Energy Sharing in Smart Grids: A Game Theory Approach

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Abstract

The need for energy conservation, grid reliability, and improved operational efficiencies have led to the changes from conventional electricity grids which have "blind" and manual operations, along with the electromechanical components, to interconnected and flexible "smart grids" that ensure a bidirectional flow of electricity and information between power plants and appliances, and all points in between. This transformation is necessary to meet environmental targets, to accommodate a greater emphasis on demand response, and to support distributed generation and storage capabilities.

The smart grid infrastructure can be divided into three main components: i) the smart energy system, ii) the smart information system, and iii) the smart communication system. In this dissertation, we start our study by investigating the energy efficiency in Wireless Sensor Networks (WSNs) as key communication enablers in the smart communication system component of the smart grid infrastructure. First of all, we explore how game theory has been used to achieve energy efficiency and maximize network lifetime. The literature is surveyed at different levels: i) Power Control and Medium Access Control (MAC), ii) Routing and Clustering, iii) Coverage and Topology Control, and iv) Data Aggregation, Security, Task Allocation and Energy Harvesting. Second of all, we investigate the energy efficiency in low-data rate Wireless Multimedia Sensor Networks (WMSNs) by studying the energy consumption of the MAC layer in this kind of networks and its application scenarios in smart grids.

After that, we shift our attention to the smart energy system component of the smart grid infrastructure. We focus on maximizing the utilization of locally harvested renewable energy in the residential sector. In this regard, renewable energy sharing is proposed as a possible solution to tackle this problem. Two different energy sharing frameworks are proposed for microgrids, where game theory is used as an analytical tool. In the first one, the energy sharing between households is modeled as a repeated game. In this framework, households share their surplus renewable energy with each other directly in a distributed manner. In the second one, a reputation-based energy sharing framework for microgrids with a shared Energy Storage System (ESS) is proposed. In this framework, households share their surplus renewable energy by storing it in the shared storage unit, which manages their demand, and allocates the shared renewable energy among them based on their reputation, represented by the amount of energy they shared previously. We aim at investigating how game theory can increase the efficiency of energy sharing frameworks in smart grids by modeling households' interactions and providing incentive mechanisms for cooperation. It is expected that this dissertation will fill a gap in the area of smart grids and raise the interest to further explore and develop this promising research area.

Contents

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List of Publications

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BNE Bayesian Nash equilibrium

CD Clothes Dryer

CDMA Code Division Multiple Access

CPP Critical Peak Pricing

CSMA Carrier Sense Multiple Access

CTS Clear-to-Send

CW Contention Window

CWmin minimum Contention Window

DAP Deferred Acceptance Procedure

DERs Distributed Energy Resources

DG Distributed Generation

DoS Denial of Service

DSM Demand-Side Management

DW Dish Washer

EH-WSNs Energy Harvesting Wireless Sensor Networks

EMS Energy Management System

EPG Exact Potential Game

ESS Energy Sotorage System

FSR Frame Access Rate

ICT Information and Communication Technology

IDS Intrusion Detection System

ILP Integer Linear Programming

IoT Internet of Things

LPL Low Power Listening

MAC Medium Access Control

MER Minimum Energy Routing

MILP Mixed Integer Linear Programming

MMSs Multimedia Sensors

NBS Nash Bargaining Solution

NE Nash Equilibrium

OPG Ordinal Potential Game

P2P Peer-to-Peer

PEV Plug-in Electric Vehicles

QoS Quality of Service

RES Renewable Energy Source

RGB Red-Green-Blue

RTP Real-Time Pricing

RTS Request-to-Send

SINR Signal Interference plus Noise Ratio

SM Smart Meters

SoC State of Charge

SPE Sub-game Perfect Nash Equilibrium

SPF Shortest Path First

SSs Scalar Sensors

TC Topology Control

TDMA Time Division Multiple Access

ToUP Time of Use Pricing

WAMR Wireless Automatic Meter Reading

WLANs Wireless Local Area Networks

WM Washing Machine

WMSNs Wireless Multimedia Sensor Networks

WSLS Win-Stay, Lose-Shift

WSNs Wireless Sensor Networks

I dedicate this work to my home country Syria . . .

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1
Introduction

1.1 Motivation

Increasing energy demand, diminishing fossil fuels, the devastating risks of climate change, and ambitious emissions' reduction targets have led to significant changes in the way of producing, distributing, and consuming electricity, and called for the modernization of the power grid, in which Information and Communication Technology (ICT) plays a key role [1].

The next-generation electricity grid, known as the "smart grid", is an intelligent grid that is expected to address the major shortcomings of the conventional grid. The smart grid should ensure a two-way flow of electricity and information between power plants and appliances, and all points in between. It is required to be self-healing and enable more adaptive and resilient operation. It should provide full visibility and pervasive control over system components and functions. Smart grids are considered as a key component of sustainable smart cities, opening up for a broad spectrum of new technologies and business models to increase energy efficiency and reduce climate impact. Regardless of how quickly this transition may take, all utilities and governments agree on

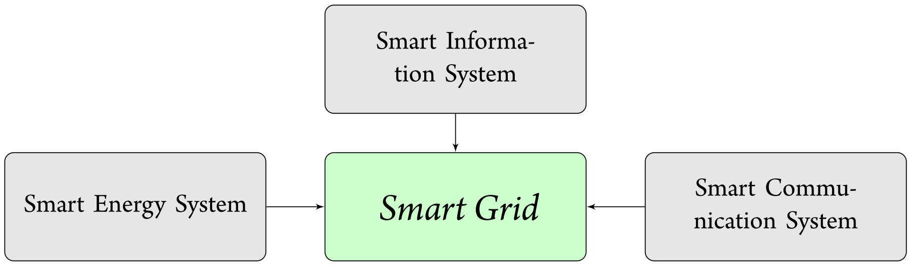


Figure 1.1.1: The main components of the smart grid infrastructure.

the inevitability of this massive transformation [1, 2].

The smart grid infrastructure can be divided into three main components: i) the *smart energy system*, which is responsible for advanced electricity generation, transmission, distribution and consumption, ii) the *smart information system*, which is responsible for information metering, monitoring, and management, and iii) the *smart communication system*, which is responsible for communication connectivity and data exchange between systems, devices, and applications [2]. Fig. 1.1.1 shows the main components of the smart grid infrastructure.

Further developing the architecture of smart grids, the microgrid concept is defined as interconnected networks of Distributed Energy Resources (DERs) (e.g., solar PV panels), loads (e.g., households), and storage (e.g., batteries) that can function whether they are connected to or separated from the main electricity grid [3]. To the utility, a microgrid can be thought of as a controlled cell of the power system. To the customer, the microgrid can be designed to meet their special needs, such as, to enhance local reliability, to reduce feeder losses, and to increase efficiency, among others [4]. Microgrids are considered as basic structures of the smart grid. An example of a simple microgrid scenario is illustrated in Fig. 1.1.2.

Many strategies are proposed to develop solutions for the generation and efficient usage of electricity at different levels. Demand-Side Management (DSM) is a key integral part of the concept of smart grids. It refers to the management strategies that aim to increase the involvement of end-consumers in the planning and implementation of innovative energy efficiency measures and solutions [5]. They allow end-consumers (e.g., households) to manage their electricity consumption in response to the changes in electricity prices over time, such as Time of Use Pricing (ToUP), Critical Peak Pricing (CPP), and Real-Time Pricing (RTP) dynamics, among others. In smart grids, each household is typically equipped with a smart energy meter, which monitors and controls power

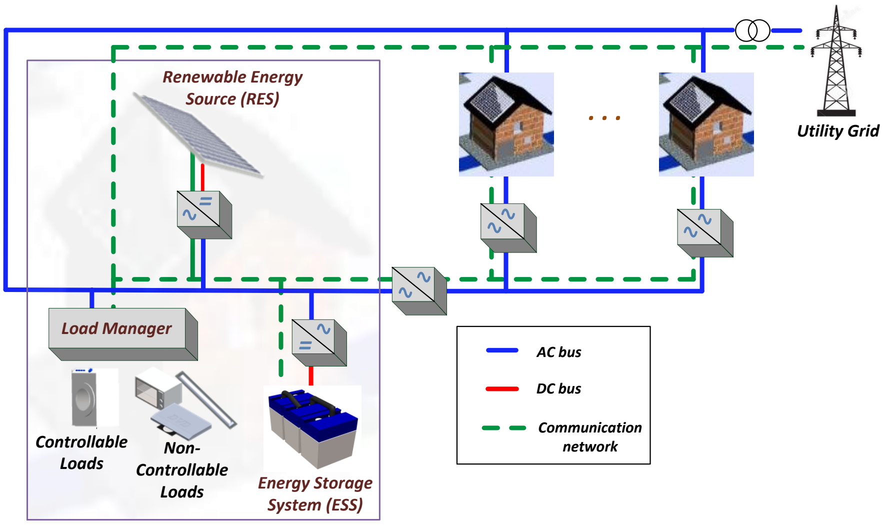


Figure 1.1.2: A microgrid scenario.

consumption intelligently. Besides, Smart Meters (SM) are responsible of data communications between households and the main grid and/or between households themselves. They exchange information about households' demand and electricity prices at each time slot. Based on the readings of SM, each households in RTP programs, for instance, is expected to individually respond to time-varying electricity tariffs by scheduling controllable demand at times when electricity prices are cheap.

The integration of DERs solutions can bring further reduction in power demands in the residential sector. Many households and residential buildings are beginning to adopt small-scale on-site renewable energy production sources, such as solar panels. However, as renewable energy is intermittent due to its nature, they keep connected to the main grid to secure their power demand during times of the day when renewable energy generation is impossible due to external weather conditions [3].

In the following section, we will present and discuss some problems related to the different components of the smart grid infrastructure (see Fig. 1.1.1).

1.2 Research Problem

Recent advances in Wireless Sensor Networks (WSNs) made it possible to realize low-cost monitoring, diagnostic and automation systems for smart grids [6–8]. In these systems, sensor nodes are used to monitor critical smart grid equipment and respond to changing conditions in a proactive manner. The opportunities and design challenges of WSNs for smart grid applications have been presented in [9]. Since it is usually difficult and costly to replace faulty sensors once they are deployed, improving energy efficiency and maximizing the network lifetime is of paramount importance. This can be achieved at different levels related both to the smart information system, and the smart communication system, of the previously mentioned smart grid's infrastructure, such as, data management, routing, clustering, Medium Access Control (MAC), coverage and topology control, among others. Therefore, investigating the energy efficiency at the different levels of WSNs is an important problem to address.

As mentioned before, the smart energy system is responsible for advanced electricity generation, transmission, distribution and consumption. Regarding the consumption side, it has been observed that a large portion of electricity is consumed in the residential sector [10]. Hence, involving citizens in the efficient planning and use of electricity is key. Households may have different power demand profiles due to various factors such as occupants' social grade and employment status, as well as the number and age of occupants. Assuming that households in microgrids have an on-site small scale DER, the time when renewable energy is harvested and the time of households' power consumption do not necessarily overlap. As a result, a mismatch occurs between the local generation of renewable energy and power consumption in some households, which reduces the utilization of DERs.

Using energy storage [3], and injecting the surplus renewable energy into the grid [11] are among the possible solutions that increase the benefit of adopting on-site DERs. However, equipping each household with an on-site Energy Sotorage System (ESS) might be economically unaffordable due to the high cost of batteries which are required to buffer sufficient renewable energy for an average household daily power consumption [12], such as the recently announced Tesla Powerwall battery [13]. Besides, batteries with long cycle life have a big physical size that makes them difficult to be located inside houses (e.g., Vanadium Redox-flow batteries [14, 15]). On the other hand, reinjecting power from unpredictable DERs, such as solar energy, into the main grid at a large scale (i.e., exceeding a certain limit) may cause grid instabilities. For instance, there are strict laws in the U.S. that limit the total number of participating households that can inject renewable energy into the grid [11].

Considering the fact that households' electricity consumption patterns do not necessarily overlap, an alternative possible solution to maximize the potential of DERs is to allow households to *share* their renewable energy among each other in a cooperative fashion. This can be achieved assuming, as mentioned before, that each household will be equipped with a SM responsible on monitoring, control, and data communications. Recently, energy sharing mechanisms in smart grids and microgrids have received significant attention [16–19]. In [16], a shared energy storage framework is proposed for the cost savings trade-off problem among multiple users in a demand response system using a Markovian model. The work presented in [17] uses a greedy matching algorithm to determine which households should share energy in order to reduce energy losses. [18] analyzes the trade-off between the use of storage and the cooperation, represented by exchanging energy among the distributed sources. The problem is formulated as a stochastic optimization problem with the objective of minimizing the cost of energy exchange within the grid. A Peer-to-Peer (P2P) energy sharing framework between multiple neighboring microgrids is proposed in [19]. It extends the work presented in [18], and handles the mismatching problem between local demand and local generation. It proposes an optimization problem that aims at minimizing the P2P energy sharing losses in a distribution network consisting of multiple microgrids, taking power balance and battery's operational constraints into account.

While interesting, the existing energy sharing frameworks in the literature focus on the optimization of energy sharing process by reducing the losses accompanied with energy exchange between entities in smart grids (e.g., households or entire microgrids). It is assumed that all entities are always willing to share energy with each other which might not be very practical since some entities are reluctant to cooperate and share energy; others are willing to receive energy more than they contribute. Therefore, flexible and robust energy sharing frameworks, that allows entities to make intelligent decisions about sharing and distributing energy with each other, and dynamically adapt to changes within the system, are required. We believe that such frameworks will greatly increase the efficiency of the smart energy system in smart grids.

Game theory has been used recently in a remarkable amount of research in this area, since it provides efficient analytical tools to model interactions among entities with conflicting interests and in a distributed manner [20, 21]. It has been used to address a broad spectrum of challenges in smart grids. Game theory and its application in smart grids and wireless networks will be discussed and summarized in Chapter 2.

In this dissertation, we start our work in the smart communication system, the third component of the smart grid infrastructure. We investigate and survey how game theory has been used to increase energy efficiency and prolong network lifetime in WSNs. Then, we study the energy efficiency in low-data rate Wireless Multimedia Sensor Networks (WMSNs), by focusing on the energy consumption models of the MAC layer, since the radio is considered as a major source of energy consumption.

After that, we move to study the problem of maximizing the utilization of local DERs in households, which is related to the consumption side in the smart energy system. To do that, we use a game theory approach in two proposed energy sharing frameworks for microgrids. We aim at investigating how game theory can increase the efficiency of energy sharing frameworks by modeling households' interaction and providing incentive mechanisms for cooperation in order to punish selfish households that want to receive more energy and save their own resources. These mechanisms guarantee that all households will receive energy in proportion to their level of cooperation. To the best of our knowledge, the work presented in this dissertation is the first work to investigate the usability of a game theory approach in the design of energy sharing frameworks for microgrids.

1.3 Contribution

The contributions of this dissertation are summarized as follows: Firs of all, we focus on WSNs as key communication enablers of the smart communication system in smart grids. We explore how game theory has been used to achieve energy efficiency in the sensor network and maximize its lifetime. The recent research studies in this area are presented and discussed. The literature is surveyed at four levels: i) Power Control and MAC, ii) Routing and Clustering, iii) Coverage and Topology Control, and iv) Data Aggregation, Security, Task Allocation and Energy Harvesting. Each level is further divided into three parts based on the class of games used. In each level, the papers are summarized in a table which illustrates the class of the game used, the game solution strategies, and the energy savings methods applied. The survey is also supported by statistical charts that overview how this research area has evolved in the last few years. This work is presented in Chapter 3. It provides a brief but comprehensive view of the state of the art in all aspects of this research area, and sheds the light on its main current challenges and future trends.

Second of all, we investigate the energy efficiency in low-data rate WMSNs by modeling and evaluating the energy consumption of the MAC layer. We conduct this study motivated by the fact that some applications can be enhanced by adding Multimedia Sensors (MMSs) able to capture and transmit small multimedia samples such as still images or audio files [22]. These applications vary from objects tracking and monitoring to intruders detection, which could be applied in distributed energy generation farms (i.e., solar and wind farms), ESS, smart houses and buildings, among others. We investigate and compare the energy efficiency of various baseline and recent MAC protocols in this kind of networks and applications. For this purpose, we develop a general sensor network traffic model which allows integrating different types of sensors with different sampling rates. This model helps to analyze the effects of various parameters of MMSs -such as the sampling rate, the size of multimedia sample and the density of MMSs- on the traffic each node transmits, receives and overhears. The main goal is to evaluate how the considered MAC protocols perform in WMSNs from an energy efficiency point of view, and to recommend the most suitable ones for this kind of networks and its applications. This work is presented in Chapter 4.

After that, we shift our focus to the first component of the smart grid infrastructure, namely the smart energy system. We aim to address the problem of maximizing the utilization of households' local DERs in microgrids. First of all, we propose a distributed energy sharing framework, where households can cooperate and share their surplus renewable energy in an intelligent and harmonized manner. The interaction between rational households is modeled as a repeated energy sharing game, in which households can reduce their demands from the main grid by exchanging some amount of renewable energy among each other. In repeated games, players interact with each other for multiple rounds, in contrast to one-shot games (see Chapter 2), and each time they play the same game. In such situations, players have opportunities to adapt to their opponents' behavior (i.e., learn) and try to become more successful, which is very useful in the proposed distributed energy sharing game. The economical and environmental potentials of this proposed framework are assessed. The economical potential is expressed as the cost savings of households' power demand, and the environmental potential is expressed as CO_2 emissions' reduction per kWh of electricity demand. Simulation results presented in this work are based on real pricing data, and real solar energy and demand profiles for households of different sizes and consumption profiles. The work is presented in Chapter 5.

Second of all, a novel reputation-based energy sharing framework that uses a shared ESS is proposed. In this scenario, households store all their surplus renewable energy in a shared battery, that is controlled by an Energy Management System (EMS). The EMS, in turn, manages the battery and reallocates the available shared renewable energy in a fair and efficient manner. A reputation-based energy allocation policy is proposed, which belongs to incentive-based mechanisms in game theory. The basic idea for incentive-based mechanisms [21] is to identify players based on their behavior. Players that offer resources should be rewarded. On the other hand, selfish players should be gradually isolated from the system. Reputation-based systems are one of the main concepts of incentive mechanisms. A player's reputation reflect its willingness to cooperate and share its resource. Reputation systems are a good application in energy sharing framework in microgrids, where there exists various classes of households with different power consumption profiles.

According to the proposed policy, the EMS determines the portion of power that will be allocated to each household based on its reputation. We apply this framework in an appliances power scheduling optimization system, in which households' appliances are not only scheduled at times when electricity tariff are cheap, but also are allowed to use the available energy scheduled by the EMS, taking battery's operational constraints into account. We formulate the appliances power scheduling problem using Mixed Integer Linear Programming (MILP), with an objective of minimizing the appliances demand costs. The main contribution in this problem is that the benefit of the shared ESS and the reputation-based energy allocation mechanism are taking into account in the objective function. Besides, power balance and battery's operational constraints are also considered. The fairness and the economical potential of the proposed system are verified via simulations in different scenarios and using real data of renewable energy and appliances demand profiles, as well as pricing data. This work is presented in Chapter 6.

1.4 Thesis Roadmap

The rest of the dissertation is organized as follows. Chapter 2 presents an overview of smart grids and provides a taxonomy of game theory. It shows how game theory has been applied recently in smart grids and wireless networks. It also gives an overview of WSNs, WMSNs and their MAC protocols. Chapter 3 provides a survey of game theory for energy efficiency in WSNs. A comparative study of the energy efficiency of MAC protocols in low data rate WMSNs and their applications is conducted in Chapter 4. After that, we address the energy sharing problems using game theory. In Chapter 5, a distributed energy sharing framework among households in microgrids via a repeated game approach is presented. Then, a novel reputation-based energy sharing framework that uses a shared ESS is proposed in Chapter 6. In this chapter, an energy allocation policy that is based on households' reputation is proposed in Section 6.3. After that, the problem of appliances power scheduling optimization is formulated in Section 6.5. Finally, we conclude the dissertation and provide guidelines for future work in Chapter 7.

2
Background

2.1 Smart Grids

The term grid is used to indicate the electric power network, which is responsible on electricity generation, transmission, distribution, and control. Targets like demand response, energy conservation, carbon footprint reduction, high penetration of renewable sources, improving efficiency, and enhancing reliability, cannot be addressed using the existing conventional electricity grid, and have called for the modernization of the power grid, in which ICT plays a key role [1].

Smart grids represent the transition from conventional electricity grids, where electricity flows one-way from generators to consumers, to interconnected and flexible grids that ensure a bidirectional flow of electricity and information between power plants and appliances, and all points in between. Smart grids are intelligently integrated operational and technological systems for optimizing power generation, distribution, and consumption, and is considered as a key component of sustainable smart cities. On the one hand, they provide utility companies with full visibility and pervasive control over their assets and services, opening up for a broad spectrum of new tech-

Table 2.1.1: A brief comparison between conventional electric grids and smart grids [1].

Conventional grid	**Smart grid**
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Failures and blackouts	Adaptive and islanding
Limited control	Pervasive control
Few customer choices	Many customer choices

nologies and business models to increase energy efficiency and reduce climate impact. On the other hand, they empower end-consumers to interact with the energy management system to adjust their power consumption and reduce their demand costs [1]. Many surveys can be found in the literature that focus to a great extent on smart grids architectures, challenges, communications requirements, and potential applications [2, 8, 23, 24]. A comparison between smart grids and conventional grids is provided in Table 2.1.1.

The microgrid concept refers to a set of loads (e.g., households), DERs (e.g., solar PV panels), and possibly an ESS (e.g., batteries), operating as a single controllable system that provides power to its local area. Micrograms can be considered as intelligent distribution systems with two different modes of operation: the islanded mode and the grid-connected mode. They possibly incorporate power plants capable of meeting local demand and possibly reinjecting the surplus energy back to the main grid [1, 3]. The microgrid incorporates SM and sensors capable of measuring and monitoring a multitude of parameters such as power, voltage, and current among others. Besides, a communication infrastructure is essential for a microgrid in order to enable system components to exchange information and commands securely and reliably. It also incorporates smart terminations and appliances capable of communicating their status and accepting commands to adjust and control their performance and service level based on user and/or utility requirements [1]. An example of a microgrid topology is illustrated in Fig. 2.1.1.

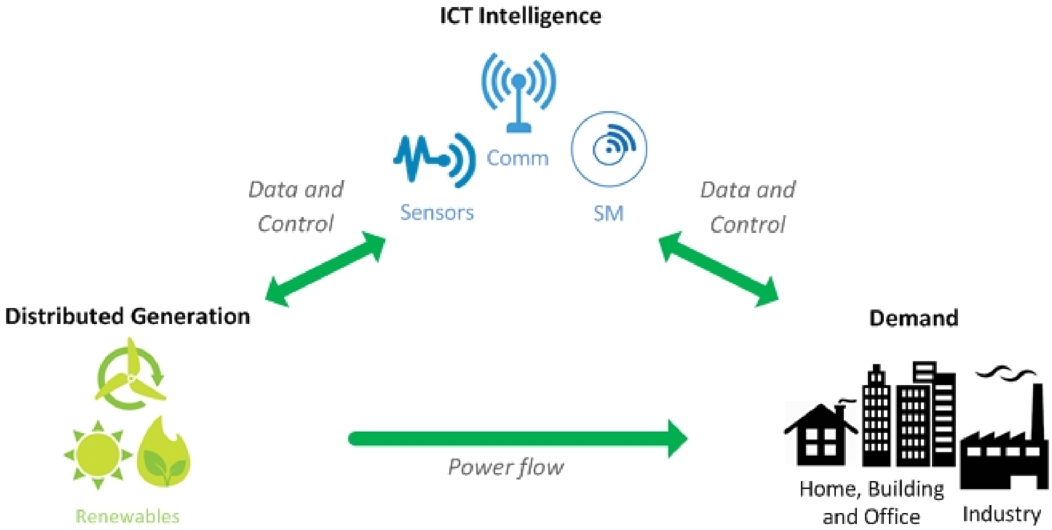


Figure 2.1.1: Microgrid topology.

2.2 Wireless Sensor Networks

WSNs have met a growing interest in the last decade due to their applicability to a large class of contexts, such as environment monitoring, object tracking, traffic control, and health applications, among others. Recent advances in WSNs made it possible to realize low-cost monitoring, diagnostic and automation systems for smart grids [6–9]. In these systems, sensor nodes are used to monitor critical smart grid equipment and respond to changing conditions in a proactive manner. Some existing applications of WSNs in smart grids include load management and control, Wireless Automatic Meter Reading (WAMR), equipment fault diagnostics, remote monitoring, electric fault detection, objects tracking and intruders detection in power plants, distributed energy generation farms and storage units, among others [9].

A *WSN* is a wireless communication network where all or most of its nodes have sensors, ranging from Scalar Sensors (SSs) that can sense voltage, current, temperature, or relative humidity to MMSs such as cameras and audio devices. WSNs is typically formed by a large number of small in size, low-cost, battery-powered and resource-constrained nodes that might be randomly disposed or strategically placed all over the region of interest. They perform certain tasks like monitoring, event detection, reports generation and communicating, likely via multi-hop wireless links, with one or more destination nodes, called the sink, which in turn is responsible on data collection, sometimes in-network data processing and possibly performing specific queries for certain information.

In some scenarios, when multiple surrounding nodes detect the same event, one of them generates a final report after collaborating with the other nodes. The sink can process that report and possibly send it out through either high-quality wireless, or wired links to external centers for further processing. Nodes are static most of the time, whereas mobile nodes can be deployed according to application requirements. A sink can also be either static or mobile, and one or several sinks could be deployed together within the same network.

The topology of sensor networks could be classified as a: (i) flat topology, where all nodes are of the same level and behave according to same rules (i.e., generating and forwarding data), (ii) cluster-based topology, in which there are different categories of sensor nodes (SNs), and cluster heads (CHs). SNs communicate mainly or exclusively to its CH -usually the closest one to itself. The network region is then divided into clusters. Each CH performs all inter-cluster communications, and might aggregate its cluster data before sending it to other CHs or to the sink.

Typically, a flat topology is used in homogeneous networks, where all nodes have the same capabilities. Cluster-based topologies are usually used in heterogeneous networks, as CHs may have more capabilities in terms of energy, communication and processing power. The use of those higher-capacity nodes can greatly increase the network reliability and lifetime but imposes additional cost and challenges like deciding how many CHs should be existed in the network and how they should be deployed, and in most cases require specific routing protocols. The reader can refer to [25–27] for further reading about WSNs.

2.3 Wireless Multimedia Sensor Networks

Different smart grid applications, such as remote monitoring, controlling and intruders detection in power plants, distributed energy generation farms (i.e., solar and wind farms) and storage units, smart houses and buildings, among others, can be enhanced by adding MMSs able to capture and transmit small multimedia samples such as still images or audio files. The potential applications and challenges of employing WMSNs in smart grids have been surveyed in [22].

In this kind of WMSNs [28], maximizing the network lifetime is of a paramount importance. To achieve this goal, using an energy efficient MAC protocol is key since the radio is a major source of energy consumption in the sensing nodes [29]. The MAC layer coordinates nodes' access to the shared wireless medium. Doing so in an energy efficient way becomes more complicated when nodes of different sampling rates exist in the network and generate different traffic loads.

Based on applications, WMSNs' traffic can be classified into two main categories, multimedia streams (e.g., video streaming) and multimedia data (e.g., snapshot multimedia content). Each of these categories can be further classified, according to the level of Quality of Service (QoS) required by the overlying application, into real-time and delay-tolerant [28]. Multimedia streaming applications put a lot of effort on achieving high bandwidth for a steady flow of data while real-time applications require a delay-bounded delivery of packets. In these cases, energy efficiency is of a lower priority. However, these applications are out of the scope of this study. In our dissertation, we focus on non-streaming and delay-tolerant WMSNs that require relatively lower bandwidth demands than streaming ones [28]. This includes a wide range of monitoring applications in smart grids, where on the one hand it is essential to keep monitoring the field or grid components, but on the other hand the phenomenons' observation is delay-tolerant and the generated multimedia traffic is lower -compared to multimedia streams. In this kind of applications MMSs can be deployed to sporadically send still-images or audio files (e.g., images about structural health in a territory, crops status in vineyards, pets and children in a house, sounds and noise in bar zones, among others). This imposes a higher traffic load compared to the typical WSNs where only SSs -which sense scalar data and physical attributes (e.g., temperature and humidity readings)- are deployed, and it directly affects the energy efficiency of the MAC layer.

2.3.1 Medium Access Control

The design and implementation of MAC protocols in WSNs have been strongly related to the requirements of applications enabled by sensing nodes. Classical MAC protocols have been originally designed for applications that handle scalar data only. Other MAC protocols have been later developed for more sophisticated applications that usually require a steady flow and/or a real-time delivery of packets. Such applications typically demand high throughput, bounded delay, and high reliability. In this section we will review the two groups of MAC protocols, though later, in Chapter 4, we will model and evaluate the ones designed for the first group only, since the set of applications we are considering does not require any streaming support. We believe that using streaming MAC protocols in non-streaming and delay-tolerant WMSNs would increase nodes' energy consumption for an undesired service.

The main categories of MAC protocols in WSNs

MAC protocols for scalar WSNs have been classified in various categories based on when and how nodes decide to transmit data. These categories are: asynchronous (or random access), synchronous (locally or globally), and hybrid [29–31]. In general, successful transmission and reception, idle listening, collisions, and overhearing are the major sources of energy consumption of MAC protocols in WSNs. Research work have focused on how to improve the performance of MAC protocols in a way the energy wasted in idle listening, collisions, and overhearing is minimized. To reduce idle listening, the duty cycling technique has been widely adopted. With duty cycling, nodes switch periodically between active and sleeping states. In the asynchronous category, each node decides when to wake up autonomously, given the rules defined by the particular MAC protocol, and the duty of the MAC protocol is to establish communication between nodes. Asynchronous MAC protocols for WSNs include: B-MAC [32], X-MAC [33], RI-MAC [34], and PW-MAC [35], among others.

Another category of MAC protocols is the synchronous MAC protocols. This category is further divided into two main branches: locally synchronized and globally synchronized (i.e. frame-slotted) [29]. Locally synchronized MAC protocols (e.g., S-MAC [36] and T-MAC [37]) also adopt the duty cycling mechanism. To save energy, they allow nodes to turn off their radio when no communication occurs during a certain time period. They differ from asynchronous MACs in the sense that each cluster of neighboring nodes are scheduled to wake up at the same time. Frame-slotted MACs (e.g., L-MAC [38] and TreeMAC [39]) divide time into frames and assign time slots to nodes in a way that no two nodes within the two-hop distance are allocated the same time slot. The problem of synchronous MAC protocols is that they require to keep the network synchronized which implies a high control overhead.

QoS-aware MAC protocols in WSNs

The deployment of resource-constrained sensing nodes in critical environments (e.g., real-time applications) impose additional challenges on the MAC layer in order to assure a certain level of QoS required by the application. For instance, a MAC protocol has to be flexible and dynamic to changes in the network, minimize the medium access delay by minimizing collisions, and maximize reliability by minimizing traffic losses. There are several examples of MAC protocols in the literature that support QoS metrics such as Q-MAC [40], RL-MAC [41], PQ-MAC [42], CoSenS

[43], among others. The QoS-aware MAC protocols for WSNs and WMSNs have been surveyed and classified in [44].

MAC protocols for streaming WMSNs

Designing a MAC protocol for streaming WMSNs is a complicated task since they require a steady flow of data, in addition, to a delay-bounded delivery of packets, which might be very challenging for any category of MAC protocols mentioned in Section 2.3.1 (e.g., due to the increasing probability of collisions in asynchronous MACs, or the limited slots' duration in synchronous MACs). There are several considerations when designing a MAC protocol for video streaming WMSNs which are summarized in [45]. For instance, nodes need to implement intra- and inter-node traffic class differentiation in order to separate traffic according to its classes and serve each class based on its priority. Intra-node traffic class differentiation is achieved by adding queuing management and priority control mechanisms. Inter-node traffic class differentiation requires Contention Window (CW) size control which allows senders to assign a shorter CW to high priority traffic and a larger CW to low priority one. These mechanisms can significantly reduce latency for streaming traffic but at the cost of an increased complexity in the protocol design and low fairness guarantees for nodes with low priority traffic. Saxena [46] is an example of a MAC protocol designed to offer QoS for video streaming WMSNs. The protocol dynamically controls the CW size and duty cycle based on some collected network statistics from the node and the medium such as traffic classes and transmission failures. It shows high adaptive operation to network changes but it causes low-priority traffic to suffer from high latency. In addition, there is no local or global synchronization between nodes which introduces significant idle listening and early sleeping problems [44]. Diff-MAC [47] is another QoS-aware MAC protocol designed for WMSNs with heterogeneous traffic classes by adopting a service differentiation mechanism. In this protocol, long video frames are fragmented into smaller video packets and transmitted as bursts. The CW size and the duty cycle of the node are also adjusted according to the traffic class. The protocol provides fair and fast delivery of data and adapts fast to changing network conditions at the cost of the overhead introduced by service differentiation mechanisms and network monitoring statistics. It also suffers from a lack of sleep-listen synchronization between neighboring nodes [44].

MAC protocols for low data rate WMSNs

After providing an overview of application-specific MAC protocols, it is clearly observed that existing WMSNs' MAC protocols pay much attention to streaming and real-time applications. However, non-streaming and delay-tolerant traffic class of WMSNs may not require a complex design of MAC protocols like streaming and real-time WMSNs, though they generate higher traffic load than scalar WSNs due to the existence of MMSs. On the other hand, WSNs' MAC protocols have been originally designed for scalar sensors with low bandwidth demand and with energy efficiency considerations. Since our focus is on non-streaming and delay-tolerant WMSNs applications, we believe that those WSNs MAC protocols are the best candidates for our applications. Therefore, the main purpose of this study is to model and evaluate the energy consumption of those MAC protocols in such scenarios. The MAC protocols are selected to be from different categories, such as receiver-initiated and sender-initiated asynchronous MACs, as well as locally and globally synchronized MACs. Then, from each category we choose baseline and recent MAC protocols.

The considered WMSNs include a wide spectrum of applications such as object detection, monitoring and tracking applications. In such applications, a WMSN works typically at very low data rates where collisions are of a little concern [27, 30]. Nevertheless, this could be safeguarded by bounding the maximum traffic flowing through the network (as we will see later). For instance, in structural health or in crops status in vineyards monitoring applications, MMSs are deployed to send images of buildings/crops. By keeping an archive of images and comparing them with images obtained in different time periods, an improved management/a better productivity could be achieved. However, since the status of these monitored objects is not commonly changing over short periods and does not require a real-time delivery of data, there is no need to sample the environment at high or medium data rates.

Platforms for low data rate WMSNs

Several hardware and software platforms have been devised to serve those applications. Cyclops [48] is an imaging platform designed specifically for energy-efficient WMSN applications. It uses a frame differentiating and a background subtraction techniques for detecting moving objects and a low resolution (images of 128x128, 64x64 and 32x32 pixels) to reduce the amount of traffic transmitted. Other platforms that support similar features are Senseye [49] and Firefly [50]. XYZ-ALOHA [51] is another platform that integrates the XYZ networking node with the ALOHA imager. The ALOHA imager outputs metadata (i.e., Address Event Representation) instead of coded images, minimizing the amount of traffic sent towards the sink.

2.4 Game Theory

Game theory [20], a branch of applied mathematics initiated more than sixty years ago, has been mainly studied and applied in a broad range of areas from economics, politics, sociology, and more recently in communication networks [21, 52–54] and smart grid applications [55]. The recent popularity it has been enjoying in engineering has to do with fact that it brings new perspectives to optimization and control of distributed networks. Game theory provides potential analytical tools to model interactions among entities with conflicting interests. The field was born with the book by John von Neumann and Oskar Morgenstern, [56], although the theory was developed extensively in the 1950s by many among whom John Nash, [57, 58]. Game theory mathematically describes behavior in strategic situations, in which an individual's success in making choices depends on the choices of others. It incorporates paradigms such as Nash Equilibrium (NE) and incentive mechanisms, which can help in quantifying individual preferences of decision-making agents. In fact, game theory provides a rigorous mathematical framework for modeling actions of selfish individual or cooperating agents/players. Furthermore, it has an inherently distributed nature and provides a foundation for developing distributed algorithms for dynamic resource allocation [54]. The following subsections will provide a brief overview about the various classifications and different concepts of game theory which are illustrated in Fig. 2.4.1.

2.4.1 Main Classification of Games

In general, games have been classified in different ways in the literature. The main classification of game theory divides the games into two main classes *Non-cooperative games* and *Cooperative games*. In our study we added a new class to the existing classification: *Cooperation Enforcement games*. We found that there is a significant amount of studies which fall under this class, thus we hope that it will provide to readers a good understanding of game theory models. *Mechanism design* is also considered as an advanced branch of game theory, which we are also going to explain later in this chapter. In the following subsections we describe the different concepts in each class with examples from communication networks and smart grids.

Non-cooperative Games

This class of games focuses on each player's individual utility, in response to the actions of all other players, rather than the social outcome. The stable outcomes of non-cooperative selfish agents interactions correspond to NE. In non-cooperative games individual players may act selfishly (i.e., deviate alone from a proposed solution if it is not in their interest, and do not coordinate their actions with other players). For instance, a household in a energy sharing framework in a microgrid will probably act selfishly for the following reason: from a household's point of view, sharing its renewable energy reduces its own resources. Therefore, it may not be of the household's interest to share all the available renewable energy. In contrast, if it rejects sharing energy with its neighbors, it may not receive any amount of renewable energy in future time periods when it is needed and will negatively affect its cost saving strategy. The technical report presented in [59] explains how situations of this kind can be modeled by using game theory.

In general, a game consists of three components: i) a set of participants, called *players*, $\mathcal{N} = \{n_1, \ldots, n_N\}$, where $N = |\mathcal{N}|$ is the number of players participating in the game (e.g., a set of households in a microgrid), ii) a set of available actions for each player called *strategies* $\mathcal{S} = \{s_1, \ldots, s_S\}$ (e.g., the decision to share energy or not), and iii) an associated amount of benefit or gain each player receives at the end of the game, called *payoff* or *utility* $\mathcal{U} = \{u_1, \ldots, u_U\}$, which is a function that measures the degree of satisfaction from each available strategy in terms of the considered performance metrics (e.g., cost savings of a household, energy efficiency, delay and/or target signal-to-noise ratio of a node in a communication network). Each player tries to choose his best available action (i.e., the one which gives a player the highest payoff, called *best response*). The best action for any given player depends, in general, on other players' actions. Thus, when choosing an action, a player must take into account actions other players may choose.

NE is a central solution concept in game theory. It captures the notion of a stable solution, from which no single player can individually improve his welfare by deviating [20]. Formally, a strategy vector $s \in \mathcal{S}$ is said to be a NE, if for any player i, and for each of its strategies $s_i' \in \mathcal{S}$, we have that:

$$u_i(s_i, s_{-i}) \geq u_i(s_i', s_{-i})$$

NE represents a certain stable operating point that is robust to unilateral deviations. It might not be the best operating point, but it is at least the one which all players agree on. Nash theorem says that every finite game in strategic form has NE in either mixed or pure strategies [58]. A game has

NE in a *pure strategy*, when each player deterministically plays his chosen strategy. When players are allowed to randomize and each player picks a certain probability distribution over his set of strategies, such a choice is called *mixed strategy*. In the previous example, the strategy profile when each household (player) rejects sharing energy with its opponent is a pure strategy NE.

One method for identifying the desired NE point in a game, and ensuring that the solution maximizes the utilities for both players is to compare strategy profiles using the concept of *Pareto-optimality* [59]. In a Pareto-optimal strategy profile, the payoff of a given player can not be increased without decreasing the payoff of at least one other player. A game can have several Pareto-optimal strategy profiles, and it is important to note that a Pareto-optimal strategy profile is not necessarily NE. In the previous example, the strategy profile when both household share energy with each other is Pareto-optimal, but not NE.

Potential games [20, 60] are games that admit a potential function, which in turn can be used to prove that the best-response dynamics converge to an equilibrium point. Potential games pose many interesting properties. For example, a pure strategy NE always exists. Potential games can be classified into *Exact Potential Game (EPG)*, when a given player switches from an action to another, the change in the potential function equals the change in the utility of that player, and *Ordinal Potential Game (OPG)*, when the changes in the potential function and the changes in the utility of that player are positive.

Cooperative Games

In contrast to non-cooperative games, cooperative games consider the utility of all players with the goal of maximizing the entire social payoff while maintaining fairness. The objective of cooperative game theory is to provide mechanisms to sustain cooperation among agents willing to cooperate. The main question is how the benefits and the costs of a joint effort can be divided among participants, taking into account individual and group incentives, as well as various fairness properties [20].

Cooperative game theory is also known as *coalitional game theory* which is designed to model situations in which players form groups (i.e., coalitions) rather than acting individually. A central notion in coalitional game theory is *the core*. The core is the set of payoff allocations that guarantees that no group of players has an incentive to leave its coalition to form another one. Therefore, if it is possible to find a core in a coalitional game, no coalition will break away, and it will choose the

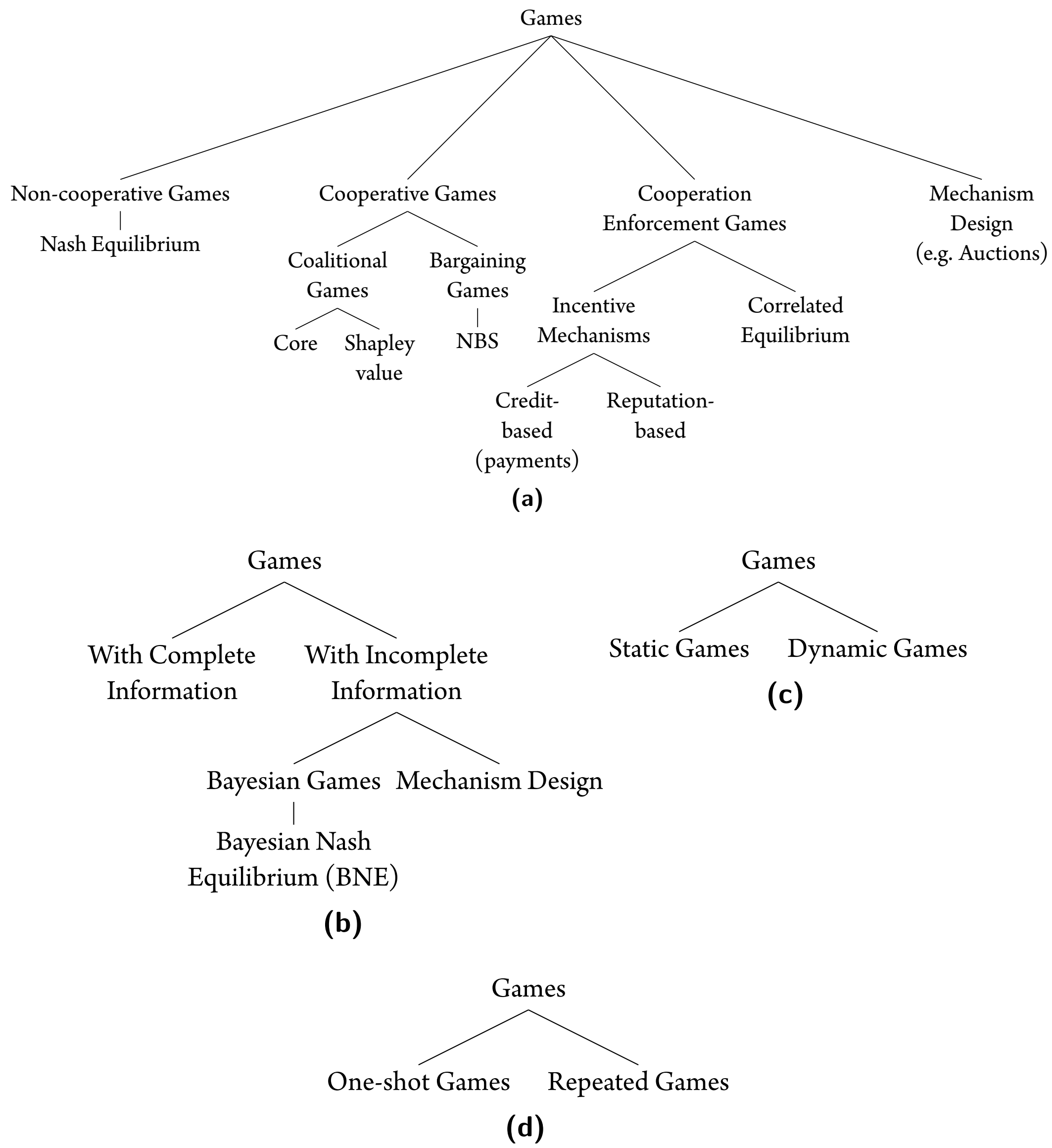


Figure 2.4.1: Taxonomy of games and the different methods to solve them, (a) cooperative, non-cooperative or cooperation enforcement games, (b) with complete information or with incomplete information, (c) static or dynamic games, (d) one-shot or repeated games.

action that all of its members prefer. In addition, by repeating the coalitional game, a certain "stable" state is achieved, where no player can improve its utility in next repetitions [53]. However, the core solution can suffer from some drawbacks, like having an unfair allocation, being empty, or being difficult to achieve, among others.

The other solution concept for coalitional game theory is the *Shapley value* [61], which is one of the efficient solutions that are used in many studies which we will present later in this chapter. However, the complexity of calculating the Shapley value increases as the number of players increases, therefore it is recommended only for coalitions with low number of players.

Another widely applied concept of cooperative games is *bargaining games*. The bargaining problem studies situations where two or more players need to select one of many possible outcomes of a joint collaboration. For example, players try to come to an agreement on a fair resource sharing inside a cluster. If the individuals reach an agreement, both of them can gain a higher benefit than playing the game without cooperation. The solution of this type of games is called *Nash Bargaining Solution (NBS)* [20, 62], in which no action taken by one of the individuals is imposed without the consent of the other.

The main difficulty of cooperative games is that players require to perform some extra computations and agreements between each other. However, when cooperative games are used, they usually give to the players a fair utility, allowing a noticeable improvement in energy conservation.

Cooperation Enforcement Games

This class considers players that would normally behave selfishly but they are enforced to cooperate, while still striving to maximize their outcomes from the game. Cooperation enforcement mechanisms are also designed to encourage greater cooperation by individuals. In multi-hop wireless networks, each node serves as a source/destination for traffic as well as a router to forward packets. Applying game theory in such environments raises the following question: What are the incentives for nodes to cooperate, particularly when cooperation might be accompanied by disincentives such as higher energy consumption? *Incentive mechanisms* fall under this class. They are generally divided into two main systems: *credit-based systems* and *reputation-based systems* [20, 52]. In credit-based systems, cooperation is induced by means of *payments* received every time players perform a service (e.g., when a node in a network relays or forwards a packet), and such credits can later be used by those players to encourage others to cooperate. In reputation-based systems, a *reputation* value is assigned to players in the system. Players that offer resources should be rewarded. On the other hand, selfish players should be gradually isolated from the system. As a player's reputation decreases, its neighbors may refuse to perform services for it, leading to its gradual exclusion from the system. Payments and reputations could be estimated either in a central management system or at each player individually. Players decide independently the extent of their cooperation with the system, trying to balance their reputation (too little cooperation might lead a player to become untrustworthy), and resource considerations (too much cooperation would run out players' resources faster).

Correlated equilibrium [63] is a solution method in which it is preferable for a player to follow an external correlation device, such as a trusted game coordinator. The traffic light example in [20] illustrates this concept. Imagine when two players drive up to the same intersection at the same time. If both attempt to cross, the result is a fatal traffic accident. In NE, players choose their strategies independently. In contrast, in a correlated equilibrium, a coordinator can choose the strategies for both players. For example, the coordinator can randomly let one of the two players cross with a certain probability. The player who is told to stop has a zero payoff, but he knows that attempting to cross will cause a traffic accident. Correlated equilibrium requires joint computation of strategies. In general, it is easier to compute those joint strategies, and finding a correlated equilibrium is polynomially solvable. However, finding an "optimal" correlated equilibrium is computationally hard [20]. Besides, it needs a third party to observe and control the interaction of players.

Mechanism Design

Mechanism design [20, 53] is an advanced class of game theory which aims to design games that have dominant strategy solutions leading to a desirable outcome (i.e., either socially desirable, or desirable for the mechanism designer). The idea is to run an algorithm in an environment with multiple owners of resources. This algorithm takes into account the preferences of the different owners. In fact, the larger goal of mechanism design is often to design mechanisms in which the selfish behavior of players leads to such socially optimal outcome. Mechanism design could be with money (e.g., auctions), like Vickery-Clarke-Groves mechanisms [20], or without money, like House Allocation problem [20]. It is analogous to Bayesian games [20] in terms of privacy of owners information, but mechanism design makes the solution of a game much simpler.

2.4.2 Other Classifications

Game theory also classifies games according to other criteria, such as if games are *static* or *dynamic*. In static games, it is assumed that there exists only one time step, which means that players move their strategy simultaneously without any knowledge of what other players are going to play. In dynamic games, players move their strategy in predetermined order, meaning that the move of one player is conditioned by the move of the previous players (i.e., the second mover knows the move of the first mover before making his decision).

A game could be further classified into one of the following two categories: a game with *complete information* or a game with *incomplete information*. In a complete information game, each player has all the knowledge about others' characteristics, strategy spaces, payoffs, and so forth, but all these informations are not necessarily available in an incomplete information game. In games with incomplete information, the overhead resulting from information exchange is reduced, because each player predicts the strategies of other players. The resulting NE of this class of games is usually called *Bayesian Nash equilibrium (BNE)* [20].

Furthermore, games could also be classified as *one-shot Games* or as *repeated games*. In one-shot games, players interact for only a single round. Thus, in these situations there is no possible way for players to reciprocate (i.e., punishment or rewards) thereafter. In contrast, in repeated games, players interact with each other for multiple rounds and each time they play the same game. In such situations, players have opportunities to adapt to each other's behaviors (i.e., learn) and try to become more successful. There can be finite-horizon repeated games, where the same game is repeated a fixed number of times by the same players, or infinite-horizon games in which the play is repeated indefinitely.

2.4.3 Game Theory in Smart Grids

Game theory has been used to address different challenges in smart grids. A survey of game theory methods for smart grids is provided in [55]. There are several studies that apply game theory models in smart grids. In [64], a distributed demand-side energy management strategy to minimize appliances demand costs using game theory is presented. In this paper, an energy consumption scheduling game is formulated, where households are the players of the game and their strategies are the daily schedules of their appliances. A distributed load management scheme based on a congestion game is proposed in [65]. The goal is to control power demands at peak hours, and to avoid overloading both the generation and the distribution capacity of the grid. To reduce electricity costs and peak loads, an RTP-based power scheduling scheme for residential power usage is proposed in [66] using a Stackelberg game model. In [67], a non-cooperative load balancing game among power demanding consumers and a retailer is formulated with two pricing schemes: an average-cost and an increasing-block pricing schemes. A Stackelberg game between utility companies and end-users is presented in [68]. The goal is to maximize the revenue of each utility company and the payoff of each-user. In [69], demand-side users are interested in minimizing their power costs by owning some kind of distributed energy source and/or energy storage device. A non-cooperative game is introduced to optimize their production/storage strategy. Two models of dynamic pricing are presented in [70] to solve the profit maximization problem of non-cooperative utility companies in a monopolistic market. In [71], a game theory based real-time load billing scheme is proposed to effectively convince selfish consumers to shift their peak-time consumption and to fairly charge the consumers for their energy consumption. A game theory based match-making solution that harmonizes load demands with the instantaneously available power, as well as the amount of stored renewable energy in smart grids is proposed in [72]. A coalition game is presented in [73] to allow consumers not only to maximize their cost savings (i.e., by scheduling their power consumption), but also to consider the social welfare in the network as well.

It is clearly noticed that different types of games are being widely used to solve various problems in smart grids. In the following chapters, we will study and show how game theory can be very helpful in increasing the efficiency in smart grids and microgrids by offering analytical tools to model players interactions and providing incentive mechanisms for cooperation.

3

Game Theory for Energy Efficiency in Wireless Sensor Networks

3.1 Introduction

This chapter provides a survey of the use of game theory to achieve energy efficiency and network life time maximization in WSNs. Since it is usually difficult and costly to replace faulty sensors once they are deployed, reducing the energy consumption in WSNs is of paramount importance in order to maximize network lifetime [25]. The lifetime of a sensor network is defined as the time until any or a given number of sensors in the network dies. This research area has drawn a lot of attention in the last few years with many researchers developing solutions to extend nodes' battery life as much as possible. A survey that offers a comprehensive view of energy-saving solutions in WSNs while taking applications' requirements into consideration is presented in [74]. So far, different approaches and mathematical methods have been used to characterize this problem, ranging from computational intelligence and optimization methods to game theory. However, the main challenge is represented in the trade-off between energy conservation and QoS which makes the problem of energy conservation more challenging.

Game theory has been widely used in analyzing modern communication networks [52–54] since it provides analytical tools to model interactions among entities with conflicting interests that compete for the limited network resources (i.e., energy and/or bandwidth), such as resource-constrained nodes in a wireless network that might -for instance- decide not to forward packets in order to preserve their own battery [59]. In some cases, nodes may seek to optimize the overall network performance. In other cases, nodes may behave maliciously, seeking to ruin the network performance for other users [53]. Game theory offers a wide range of formulations and models that can be used to optimize node-level operations, as well as network-wide performance in a flexible manner [75]. In addition, game theory allows us to model scenarios in which there is no centralized entity with a full picture of network conditions.

Previous works done in this area show that game theory can enable an intelligent behavior in such challenging environments. The book entitled "Game Theory for Wireless Engineers" [53], presents game theoretic models and their application to modern wireless networks. [54] presents the mathematical framework and control algorithms needed to tackle various game-theoretical problems in optical networks in order to optimally allocate resources. A survey that demonstrates how game theory could be effectively applied in wireless networks is provided in [52]. It highlights the best fields under the different OSI layers for applying game theory. Furthermore, game theory is considered a preferable approach for WSNs -in comparison with other types of wireless networks- for the following reasons. Firstly, solutions designed for WSNs should be fully or partially distributed. Secondly, since nodes in WSNs are typically resource-constrained and they have conflicting interests between conserving energy in order to maximize the lifetime of the network, and between providing the required QoS. There are some surveys in the literature about using game theory in WSNs [75, 76] and ad hoc networks [77]. However, the main difference between these surveys and the one presented in this chapter is that none of the previous surveys has explicitly focused on the energy efficiency and lifetime maximization problems in WSNs. For example, [76] surveys the use of game theory in WSNs in general, without focusing on energy efficiency. [75] surveys the amount of work done using game theory in WSNs before 2008, focusing on two main domains energy efficiency and security. However, there are a considerable amount of research and valuable developments in this area in the last few years that non of those surveys covers. In addition, in this chapter we cover proposals that use various game theory concepts and models which are not mentioned in previous surveys like Bargaining games, Bayesian Nash Equilibrium, the core, and correlated equilibrium, among others.

In the following sections the recent research studies employing game theory to improve energy conservation and prolong network lifetime in WSNs are presented. The literature is surveyed at four levels: i) Power Control and MAC in Section 3.2, ii) Routing and Clustering in Section 3.3, iii) Coverage and Topology Control in Section 3.4, and iv) Data Aggregation, Security, Task Allocation and Energy Harvesting in Section 3.5. Each level is further divided into three parts based on the applications of non-cooperative, cooperative and cooperation enforcement games. The levels are summarized in tables which illustrate the class of the game used, the game solution strategies and the energy savings methods applied. Besides, the articles in the tables are ordered according to the year of publication. The chapter is completed with conclusions in Section 3.6. The main goal of this chapter is to provide a brief but comprehensive view of the state of the art in all aspects of this research area, and shed the light on its main current challenges and future trends. The work presented in this chapter is published and can be found in [21].

3.2 Power Control and Medium Access Control

3.2.1 Power Control

The main sources of energy consumption in WSNs are sensing, processing and communication. Among them, communication is the one that consumes most energy. Hence transmission at optimal power level is of paramount importance. The optimal transmission power level is the one that reduces interference, increases successful packet transmission and provides a desired QoS. A large variety of schemes for power control issues in WSNs have been proposed and some of which have been surveyed in [78].

However, topology control solutions which use static transmission power, transmission range, and link quality, might not be effective in real world applications. To address this issue, many distributed non-game theoretic algorithms have been proposed in the literature for dynamically adjusting transmission power level on every single node. In [79], a dynamic algorithm that considers network lifetime as an essential metric using heuristics is proposed. A distributed algorithm that is based on geometric-programming for solving the power control problem is presented in [80]. A lightweight Adaptive Transmission Power Control (ATPC) algorithm for WSNs is proposed in [81]. In ATPC, each node builds a model for each of its neighbors, describing the correlation between transmission power and link quality. This model employs a feedback-based transmission power control algorithm to dynamically maintain the link quality of individual links over time.

Game theory provides helpful distributed mechanisms that allow every single node to interact with its neighbors, and adjust its transmission power without the need of complete information about them. Table 3.2.1 lists the latest articles that use game theory in this domain. The papers are summarized and discussed in the following subsections.

Non-cooperative Games

In [82], a non-cooperative game with incomplete information is formulated to solve the distributed power control problem in WSNs. This proposal suggests 'not to transmit' at a certain game iteration when channel conditions are poor. The investigation for the existence of NE is done for two different cases: i) fixed channel conditions, and ii) varying channel conditions, using best response dynamics. It is observed that there exists a transmission power threshold and a channel quality threshold that the nodes must comply with in order to achieve a NE. Moreover, using repeated games, nodes follow the transmission strategies to achieve a NE even without presence of any third party enforcement. A system that would allow only finite number of discrete power levels is considered. A metric called distortion factor is defined to investigate the performance of such system and compare it with systems that would allow any continuous power level. This work also proposes a technique to find the power levels at which a node should transmit in order to maximize its utility and minimize the distortion. Results show that this algorithm achieves the best possible payoff/utility for sensor nodes by consuming less power.

The power control game proposed in [83] is based on a Code Division Multiple Access (CDMA) communication. It is observed that the CH/members structure in WSNs is similar to the base station/terminal structure of CDMA. The difference here is that the utility function of the game considers the node's residual energy, and is given by:

$$u_i(p_i, p_{-i}) = \mu \log_2(1 + \mathrm{SINR}_i) - c(p_i).$$

Both the pricing $c(p_i)$ and the Signal Interference plus Noise Ratio (SINR) depends on the residual energy of node i, as follows:

$$u_i(p_i, p_{-i}) = \mu log_2(1 + G\frac{h_i p_i \frac{E_{\max}}{E_i}}{\sum_{j=1 j\neq i}^{N} h_i p_i \frac{E_{\max}}{E_i} + \delta^2}) - \lambda h_i p_i \frac{E_{\max}}{E_i},$$

where G is the gain of the spread spectrum, E_i and $E_{\max}$ are the residual energy and the maximum energy of node i, respectively, $\sum_{j=1 j \neq i}^{N} h_i p_i$ is the sum of interferences node i receives. δ^2 denotes the thermal noise power of the channel, λ is a dynamic adjust pricing factor, and μ is an income coefficient.

The existence and uniqueness of the NE is proved. Simulation results show that after considering the nodes' residual energy, path gain, and transmission power factors in the design of the pricing function, the performance of the power control game significantly improves, reducing the total transmission power efficiency, saving node energy and prolonging network lifetime efficiently.

In [84], the sensing nodes are powered solely using renewable energy to replenish its stored energy. Each sensor considers its varying energy state as private information. The existence of BNE is proved. The BNE strategy of each sensor can be implemented using a threshold. If the energy state exceeds the energy threshold, the sensor transmits with a fixed power, otherwise, the sensor waits. This study shows how each sensor determines its threshold to maximize its utility function. The equilibrium of this Bayesian game model is compared with three different models: i) a distributed perfect-information model, ii) a centralized system, and iii) a random-transmission model. Results show that the Bayesian model has a performance similar to the perfect-information model, but with a lower overhead, making the Bayesian model more suitable for real applications.

In a scenario with multiple sources and with multiple receiving clusters, all sources send their information simultaneously towards CHs. Simultaneous transmission causes interference at every receiving cluster which reduces SINR. Higher transmission power results in higher SINR, but increases the energy consumption and the interference to other receiving CHs. Therefore, a non-cooperative power control game is proposed in [85], where each sensor chooses its minimum transmission power independently to minimize its own cost in order to achieve a target SINR at the CH of the receiving cluster. The game can be expressed as a cost minimization problem which is described as follows:

$$\min_{Pi} J_i(P_i, \gamma_i) = \min_{Pi} b_i P_i + c_i(\gamma^{\text{tar}} - \gamma_i)^2,$$

where $P_i = [0, P_{max}]$ is the possible range of transmission power (i.e., strategy values) for the ith user, P_{max} is the maximum allowed power for transmission, and J_i is the cost for player i. b_i and c_i are constant non-negative weighting factors. γ^{tar} is the target SINR at cluster i, and it is the same for all clusters. The existence of an equilibrium is proved, and the cost function has a minimum value at the NE point. Therefore, no player can benefit by deviating from the NE. Bounds on the source power at NE are also proved. Performance analysis illustrates the influence of interference and distance between the source and the target cluster on NE.

The work presented in [86] claims that previous works on power control in WSNs did not focus on the system convergence. From this perspective, this proposal focuses on constructing a non-cooperative game model with a convergence algorithm, called NPC, that guides nodes to converge quickly to a NE point. Power consumption is taken as the cost for the game model. The game is decentralized and nodes have provate information. Therefore, the best response choice is used to achieve NE. Then, the system convergence to the NE point is evaluated and guaranteed using the NPC algorithm. The NPC algorithm shows a remarkable optimization in energy efficiency and convergence speed, without accessing the profile of the others.

In [87], a Game theory based Energy-efficient Power control Strategy (GEPS) is proposed for cognitive sensor networks. In cognitive sensor networks, unlicensed users (secondary) share a common spectrum with licensed users (primary). Each user wants to maximize its utility function under interference temperature constraints as follows:

$$\max_{p_i} \frac{\mathrm{B}\log(1+\mathrm{SINR}_i)}{p_i+\alpha}$$

$$\text{s.t.} \sum_{i=1}^{n} h_i p_i \leq \mathrm{M},$$

where p_i is the power allocation of user i, B is the available wireless spectrum bandwidth, and M is the interference temperature limit, which is described as a threshold of the total received power at a primary user. h_i is the link gain between a secondary user i and a primary user. Both the computational and sensing energy, α, are taken into account in the energy consumption model. Simulations are done for testing the energy efficiency of the power control game. It can be found that under some conditions this game is a super-modular game [20], which means it has good convergence properties to a NE point using best response dynamics. GEPS outperforms the Game-based QoS-oriented Power allocation Strategy (GQPS) [88] in terms of energy efficiency and system utility (i.e., the average value of cognitive users' utilities). However, as the number of users increases, the system utility in GEPS decreases dramatically, while it keeps nearly unchanged in GOPS.

A Joint Channel Allocation and Power Control Game Algorithm (JCAPGA) is proposed in [89]. Power control is used to reduce network energy consumption, and channel allocation is used to reduce network interference (generated by other transmitting and receiving nodes). However, selecting different channels affects nodes' power. Therefore, this paper aims to optimize network performance through collaboratively controlling both techniques. Nodes' transmission power, network interference, and nodes' residual energy are the parameters of the model. A node with low residual energy will choose a lower transmission power. The model is proved to be an OPG in order to ensure NE. A best response strategy is considered to improve the convergence speed. Simulation results show that, in JCAPGA the channel allocation is uniform, the network interference is low, and the energy consumption is balanced.

Cooperative Games

A repeated coalitional game is presented in [90]. The motivation is that each node can likely obtain better utility by forming groups and controlling its power cooperatively rather than individually. Nodes compete with the others trying to enhance their own power efficiency subject to QoS constraints. In this work, it is preferable to maximize the number of bits that can be transmitted per watt of the consumed power with respect to SINR, rather than to maximize the throughput, according to the definition of power efficiency [91]. The problem is modeled as two-sided one-to-one matching game, in which an owner is matched with a single non-owner in order to help the non-owner to achieve improved power efficiency. Then, the game is repeated using a Deferred Acceptance Procedure (DAP) [20]. This technique produces a single matching in the core at each repetition until reaching a certain stable state. The optimal power efficiency is computed in each step via a non-linear optimization problem, as the following:

$$\max\ u_i = \frac{r_i}{\sum_{s \in S} p_{i,s}}.$$

Subject to:

$$\begin{aligned} \sum_{s \in S} p_{is} &\leq P_i^{\max} \text{ for all } i \in \mathcal{N}, \\ T_i &\leq T_i^{\max} \text{ for all } i \in \mathcal{V}, \\ \lambda_i &\leq r_i / \Lambda_i \text{ for all } i \in \mathcal{V}, \end{aligned}$$

where $r_i = \mathrm{B} \sum_{s \in S} \log_2(1 + \mathrm{SINR}_{i,s})$, r_i is the transmission rate at sensor i, and B is the bandwidth of each sub-carrier. The parameters are: the set of sensors ($\mathcal{V}$), the set of idle sub-carriers ($\mathcal{S}$) that are detected as not allocated to primary users, the transmission power constraint of sensor i ($P_i^{\max}$), and the transmission delay constraint of sensor i ($T_i^{\max}$). The variables are: sensor i's transmission power over sub-carrier s ($p_{i,s}$), and the average transmission delay (T_i), including queueing delay per packet considering an M/M/1 queue. Simulation results show that the matching in the core improves the total power efficiency more than the social optimal, though it is less fair.

In [92], tools from cooperative game theory are used to develop a formal analytical framework for a fair allocation of power among collaborating nodes in a Fusion Center (FC) based WSNs. The goal is to achieve a sequential estimation task, while at the same time maximizing the overall network lifetime. The concept of the Shapley value is used to achieve a fair power allocation among distributed nodes. Simulation results show that the proposed solution achieves the target estimation quality at the FC, in addition to an increased lifetime of the overall sensor network is increased.

A cooperative game is proposed in [93] in order to optimize data transmission of a group of nodes by forming coalitions. A mobile node may move to a new location to join a desirable group. It requests the group leader first. Then, the group leader evaluates the benefit of group membership for the node using coalitional game theory. If the membership is beneficial, the leader sends an invitation to the node. The node itself may receive many invitations and can choose the best group in their coverage area by comparing its own utility with the offered one. The correctness of the proposed protocol is proved by searching for failures in it, through evaluating all possible behaviors of sensors using the Maude tool [94]. The work proves that the core is not empty and simulation results show that any node could always save more energy by joining a group.

In [95], a power control solution based on the trade-off between energy efficiency and end-to-end delay is presented. A cooperative coalitional game is proposed to obtain a power control solution that achieves a fair distribution of the total cost among sources. It is observed that the additional energy cost function and the delay cost function are continuously differentiable (i.e., minimizing the delay is achieved by minimizing the remaining energy level). Each source node seeks to minimize its utility function of the discounted sum of the transmission power increasing cost and the source-to-sink delay cost. Shapley value is used as a solution of the cooperative allocation game. Results illustrate the impact of delay and energy cost parameters on the energy consumption associated to different coalitions. They show that selecting a larger coalition is better

Table 3.2.1: Proposals in WSN Power Control (Section 3.2.1).

Article	Year	Class of Game	Game Techniques	Method of Energy Savings
[82]	2010	Non-cooperative	NE, best response, repeated game with incomplete information	a distributed power control mechanism according to different channel conditions
[83]	2010	Non-cooperative	NE	the SINR model takes into account the residual energy of nodes
[84]]	2011	Non-cooperative	BNE, incomplete information	an energy efficient power control with reduced overhead
[85]	2012	Non-cooperative	NE, best response	optimization of the transmission power independently to achieve a target SINR
[86]	2012	Non-cooperative	NE, best response	a game with an energy efficient convergence algorithm to quickly converge to the NE point
[87]	2012	Non-cooperative	NE, best response	the computational and sensing energy are taken into account in the energy consumption model
[89]	2014	Non-cooperative	Ordinal Potential Game, best response	a joint channel allocation and power control game to reduce both the energy consumption and the interference
[90]	2008	Cooperative	coalition, core, repeated game, DAP	maximizing the number of bits that can be transmitted per Watt of the consumed power
[92]	2010	Cooperative	coalition, Shapley value	a fair allocation of power among collaborating nodes in fusion center based WSNs
[93]	2011	Cooperative	coalition, core	optimizing the transmission power of a group, and choosing the best group in terms of power conservation
[95]	2013	Cooperative	coalition, Shapley	a fair distribution of the total cooperative cost among sources, and trade-off between energy efficiency and end-to-end delay

than a smaller one in cooperative games.

Discussion and Future Directions

From the previously reviewed proposals, we notice that non-cooperative games have been preferably used for energy efficiency in power control problems. This is because sensor nodes usually do not use any information about the separate transmission power level strategies taken by other nodes, which means that control packets are greatly reduced (see [82, 84, 86]). The proposals differ from each other according to: i) which class of games and solution concepts are used, ii) how to save energy, and iii) how to converge to a stable NE point (see NPC [86], super-modular [87], and DAP [90]). Some of proposals take into account channel conditions in order to save energy [82], while others like [83] consider nodes' residual energy in the utility function. However, proposals like [90] say that it is more important to maximize the number of bits that can be transmitted per watt of the consumed power, while [87] takes computational and sensing energy also into account in the energy model. A collaborative control of both channel allocation and power control is taken into account in [89]. In [85], a cluster-based WSN with multiple receiving clusters is studied. [93] cares about optimizing data transmissions of a group. The trade-off between energy efficiency and end-to-end delay are taken into account in [90, 95]. [95] achieves a fair distribution of the total cooperative cost among sources. It is worth noting that the performance of the proposed solutions and algorithms is not evaluated in all the presented studies, except in [82, 93].

As a conclusion, we notice that there is not one single strategy or one class of games which is considered a general solution for saving energy in this domain. The applied mechanism depends on different factors like the network scenario, if it is applicable in real cases or not, and QoS constraints, among others. In future work, game theory models could be applied to address the issues of power control mechanisms in energy harvesting WSNs.

3.2.2 Medium Access Control

Reducing energy consumption is a challenge when designing a MAC protocol for WSNs. Successful transmission and reception, idle listening, collision, and overhearing are the major sources of energy consumption in WSNs [31].

Recent proposals in this domain consider the energy efficiency of a node in WSNs as a main problem to solve. For example, in order to achieve a low power operation in the asynchronous MAC category, X-MAC [33] introduces a series of short preamble packets, instead of one long preamble as in B-MAC [32]. Regarding the synchronous category, T-MAC [37] allows an adaptive length of the active periods instead of fixed sleep/active cycles as proposed in S-MAC [36]. L-MAC [38] is based on a Time Division Multiple Access (TDMA) scheme that organizes time into frames and eliminates the channel access by precisely scheduling who is allowed to transmit in each slot. Z-MAC [96] is a hybrid MAC protocol that combines some of the best features of the TDMA and Carrier Sense Multiple Access (CSMA). Z-MAC improves energy efficiency by achieving high channel utilization and enhancing contention resolution. Comprehensive studies which analyze and compare the different MAC protocols for WSNs are presented in [30, 31]. Finally, LWT-MAC [97] is an adaptive MAC protocol suitable to be enhanced using game theory. It combines an unscheduled channel access, based on low power listening, with an opportunistic scheduled wake up after transmissions mechanism.

It is clear that each node has a direct influence on its neighboring nodes while accessing the channel. Such interactions between nodes has led researchers to use game theory in the design of MAC protocols in order to improve energy efficiency as well as end-to-end delay in a decentralized manner. Game theory has been applied in contention free categories, showing that it could save energy by decreasing collisions (e.g., Multiple Access Game [59], [98]). In the following subsections, we present and discuss the latest contributions in different MAC categories using game theory for energy savings purposes. The considered proposals in this section are summarized in Table 3.2.2. Notice that game theory has been also considered to prevent node's misbehavior at MAC layer. For instance, in CSMA/CA MAC protocols, some nodes may use different backoff parameters to get more bandwidth than the other honest contenders [99, 100]. However, since those papers do not focus on energy efficiency issues, we we do not overview them in details.

Non-cooperative Games

A simplified Game-theoretic Constraint Optimization scheme (G-ConOpt) is presented in [101], in which its performance is optimized in an energy efficiency manner. In G-ConOpt, time is divided into super-frames and every super-frame has two parts: an active part and a sleeping part. During the active part, each node plays a game and contends for the channel. During the sleeping part, each node turns off its radio to preserve energy. The durations of the active and sleeping parts are adjusted according to the estimated game state too. Firstly, a node estimates the current state of the game, defined as the number of its active opponents n. Secondly, the node adjusts its equilibrium strategy, the minimum Contention Window (CWmin), according to the estimated number of its opponents n. It is not required to compute the optimal value of CWmin. The final value of the CW is the optimal one, and the best strategy for a player is to set CWmin=CW/2. That is to say, GConOpt would not cause any more energy consumption. Power consumption and energy efficiency of GConOpt is compared with S-MAC and CSMA. Results indicate that the power consumption in both S-MAC and CSMA is almost constant, and increases adaptively in GConOpt with the increasing of the traffic loads. Energy efficiency in GConOpt is higher than in S-MAC and CSMA.

In [102], a MAC scheme based on p-persistent slotted ALOHA, and constructed as a non-cooperative game, is proposed in order to determine the value of the channel attempt probability p. Firstly, generalized payoffs are designed to reflect the costs of energy consumption and throughput deterioration. Next, NE is found in a closed form. Each player then has only two pure strategies: to always attempt to deliver a packet, and to never attempt it. NE is the mixed strategy. Using NE, the effect of the payoffs on the stability of a sensor network is investigated. It is observed that the set of feasible values of the payoff for saving energy shrinks as the traffic load per leaf node increases.

A Non-cooperative Duty-cycle Control Game (R-NDCG) for reducing the idle-listening time of sensing nodes is proposed in [103]. It aims at optimizing the sleep interval between consecutive wake-ups for random asynchronous wakeup MAC protocols. In this MAC scheme, the sender waits for a beacon signal from the receiver before starting to transmit. Since each sender receives beacon signals from several nodes, the data are routed on multiple paths. In this context, an optimization framework for minimizing the energy waste of the most power-hungry node is presented. Firstly an analytic model that predicts nodes' energy consumption is derived. Then, the model is used as a part of the optimization process. At the transmitter, the transmission energy model represents the sum of the energy spent to deliver data packets, and the energy spent to listen to the channel before a beacon signal is received and the contention is won. At the receiver, it is the sum of the total energy consumption spent in data packets reception, the energy spent for a beacon signal transmission, and the amount of energy consumed between the generation of a beacon signal and the reception of a packet. The objective function, the minimization of energy waste of the most power-hungry node, contains sums and products of rational terms. Thus, it is neither linear nor convex. Therefore a multi-start local search is presented first for solving the problem. The obtained solution was considered as a comparison benchmark for assessing the overall performance of the game theoretic approach. Then, a game theory based solution is proposed as follows: Let $G = [\{\mathcal{N}\}, \{\mathcal{R}\}, \{C_s^{(i)}(.)\}]$ denote the NDCG, where $\mathcal{N}$ is the set of the nodes, $\mathcal{R}$ is the set of strategies, and $C_s^{(i)}(.)$ is the cost function of user i. Each user i selects a beacon rate $r_s^{(i)} \in R$, which corresponds to the outcome of the game in terms of selected beacon signal rate (i.e., the duty-cycle). In the NDCG, each user minimizes his own cost function in a distributed way. Formally, the NDCG game can be expressed as:

$$\arg\ \min[C_s^i r_s^{(i)}]; \forall u_s^{(i)} \in \mathcal{N}.$$

The cost function of the proposed game represents a trade-off between a node's energy and the energy of any node belonging to a set of nodes producing data traffic towards the node. Since users act selfishly, the equilibrium point is not necessarily the best operating point from a social point of view. However, it is proved via simulations that NE of the distributed game achieves a desirable

Table 3.2.2: Proposals in WSN MAC (Section 3.2.2).

Article	Year	Class of Game	Category	Game Techniques	Method of Energy Savings
[101]	2009	Non-cooperative	mixed based (scheduling & contention)	history-based estimation, infinitely repeated	adjusting the transmission probability and the sleeping time of a node according to the number of its opponents
[102]	2010	Non-cooperative	contention based	mixed strategy NE	optimizing the channel attempt probability taking energy consumption into account
[103]	2013	Non-cooperative	scheduling based	NE, repeated game	optimizing the sleep interval between consecutive wake-ups (duty cycle control)
[104]	2007	Cooperative	scheduling based	NE, Pareto optimality, bargaining game	determining the optimal sleep and wakeup probabilities

result.

Cooperative Games

In [104], an optimal energy savings mechanism for a sensor node is presented. It uses a sleep and wake-up strategy for energy conservation. The node switches to sleep mode if channel quality is bad, and switches back to the active mode, from the listen and sleep modes, with probabilities $P_{\text{active,listen}}$ and $P_{\text{active,sleep}}$, respectively, at the beginning of periodic time intervals. The strategy for the first player is to select $P_{\text{active,sleep}}$. For the second player the strategy is to select $P_{\text{active,listen}}$. The payoff for the first player is the packet blocking probability P_{block} (due to the sleep mode), and for the second player is the packet dropping probability P_{drop} (due to buffer overflow). This strategy results in a trade-off between P_{drop} and P_{block}. A bargaining game is formulated to determine those probabilities under energy constraints. NE, which is Pareto optimal, is obtained as the solution of this game in order to obtain the optimal sleep and wake-up probabilities. The solution basically eliminates the selfishness of nodes that try to conserve energy at the expense of high P_{block}.

Discussion and Future Directions

We can infer from the presented proposals and Table 3.2.2, that game theory has been applied to address the energy efficiency in different MAC categories, scheduling based [103, 104], contention based [102], and mixed (scheduling and contention based) [101]. Although the number of studies in this domain is limited, we believe that they are sufficient to break the ice in this domain. In contention based categories, a non-cooperative game is used to determine the value of the attempt probability p in [102]. Most of the scheduling-based MAC categories focus on the optimization of active and sleeping intervals, which helps in saving energy and increasing network lifetime (see [101, 103, 104]).

We mention that non-cooperative games are preferably used. Only one proposal uses cooperative games with a Nash bargaining solution. However many issues still need to be addressed in this domain. For example, the use of game theory for energy efficiency in contention free MAC categories (e.g., TDMA), Hybrid MAC schemes, high data rate applications, and multi-channel MAC protocols are recommended for future work. Moreover, game theory tools are suitable to solve some problems in receiver initiated MAC protocols. For example, in this class of MAC protocols the sender waits for a beacon from its intended receiver before starting the transmission of data. If the time between sending two consecutive beacons increases (i.e., the receiver is saving energy), the probability that many senders will send to the same receiver and collide will also increase, which affects the energy level of other nodes in the network. Game theory provides tools to solve this trade-off problem and achieve both a social and a local optimum solution at the same time. Game theory may also be suitable for cross layer designs (e.g., to investigate how the design of MAC layer affects the network layer).

3.3 Routing and Clustering

3.3.1 Routing

Routing refers to determining a path for a message from a source node to a destination node. The routing problem is an attractive research area in WSNs. Generally, when attempting to optimize this problem, a lot of metrics should be taken into consideration. For modeling the cost of a transmission, some parameters at each node are considered. For example, the distance (i.e., delay and power consumption are proportional to it), remaining energy, and transmission rate of each link, etc. Thus, a good routing protocol should take these parameters into account and consider the distributed nature of WSNs.

Since most of the routing protocols developed for wired networks pursue the attainment of high QoS, they are impractical in WSNs. Thus, different non-game theory approaches have been done for energy aware routing in WSNs. Computational Intelligence (CI) based approaches have been widely applied in the domain of energy aware routing. Such approaches are usually based on Reinforcement Learning (RL), Swarm Intelligence (SW), Genetic Algorithms (GAs) or Neural Networks (NNs). These approaches are surveyed and briefly explained in [105, 106]. However, such approaches are generally based on meta-heuristics which do not necessarily converge to an optimal result, and are usually centralized (except reinforcement learning, see [106]). Besides, an offline learning phase, like GAs or offline NNs, can neither cope with changing properties of the network, nor provide an energy efficient routing scheme. Ant-based routing is a flexible technique, but generates a lot of additional traffic because of the forward and backward ants moving through the network.

Game theory has been successfully applied to different WSNs' routing and load balancing problems that consider energy efficiency and network lifetime maximization as main goals. Issues such as the presence of selfish nodes in the network have been analyzed using game theory, for instance, incentive mechanisms. The idea behind those models is that for each successfully delivered data packet, the destination node pays a credit or modify the reputation of the source in all intermediate nodes that participate in the routing game. However, each data packet transmission has a cost for each node that participates in the route. This cost is a function of the three previously mentioned parameters. Nodes -wanting to maximize their profit- will accept to be part of the path if its profit is not negative [107].

In this subsection, we summarize the latest contributions in this domain. The considered proposals are summarized in Table 3.3.1.

Non-cooperative Games

In [108], a Game Theoretic distributed Energy Balance Routing (GTEBR) algorithm is proposed to prolong network lifetime. It allows a node to make decisions whether to take part in the routes by considering its residual energy and other factors in order to make the whole network's energy consumption balanced. In this game, a node's strategy space is $S_i = \{0, 1\}$, the value 0 means that a node i chooses the strategy not relaying the data from its former hop node, and the value 1 means the opposite. A sensor node is modeled as having a mixed strategy, which means that a node can transmit the data with probability p_T and be silent with probability $1 - p_T$. The probability p_T is defined as a function of the residual energy $E_{r,i}$ and actual payoff $P_{a,i}$:

$$p_{Ti}(P_{a,i}, E_{r,i}).$$

The existence of NE is proved and the algorithm is compared with Maximum Energy Minimum Hops Routing (MEMHR) [109]. Simulation results show that the residual energy distribution is higher and the network lifetime is longer in GTEBR than in MEMHR. However, GTEBR exhibits a higher average hops which increases the delay.

In [110], game theory is used for efficiently constructing a Data Routing Tree (DRT) with an aim to prolong the lifetime of the entire WSN by minimizing the network segmentation. The resulting protocol is called Versatile Game Theoretic Routing Protocol (VGTR). In this protocol, the energy is expressed differently. Instead of expressing it with an absolute representation (i.e., using Joules), a time derivative representing the amount of remaining lifetime is used based on the past workload. The algorithm induces an energy-aware and efficient collaborative behavior to the nodes. The nodes predict the results of their actions and rotate the selection of their next hop in a calculated way. The rotation is achieved using the payoff function. A node will assign a high probability to a neighboring node (i.e., next hop) that will extend its life time. The performance of VGTR in terms of energy consumption outperforms other algorithms such as Directed Diffusion (DD) [111], and Simple Energy Efficiency Routing (SEER) [112]. Both Energy Aware Routing (EAR) [113] and VGTR attempt to balance the load between multiple paths. In addition, VGTR nodes are able to detect hot-paths and critical nodes and to minimize their utilization. In comparison with Low-Energy Adaptive Clustering Hierarchy (LEACH) [114], VGTR has a higher rate of node deaths which means that LEACH outperforms VGTR in prolonging network lifetime.

In [115], a reliable routing model against selfish nodes is proposed. The nodes should choose reliable routes that prolong network lifetime. When the distance between a node and the sink is fixed, the node should transmit to a distant neighbor in order to save the total network energy. Moreover, sending to a closer neighbor, increases the total number of hops to the sink, which also affects the reliability. For improving the reliability of transmission, shorter paths are preferred. However, it creates some hot areas in which nodes die quickly. To solve this contradiction, game theory is used. Besides, NE is reached after proving that the game is an OPG. The utility function proposed considers four factors. It is defined as follows:

$$u_i(p) = c_i(p) + r_i(p) - p_i(p) - h_i(p),$$

where $h_i(p)$ is the collision utility, $p_i(p)$ is transmission power, and $c_i(p)$ is the connectivity utility which is given as follows:

$$c_i(p) = c_i(p_i, p_{-i}) = (1 - f(\text{area}_n))/f(\text{area}),$$

where $f(\text{area}_n)$ is the area of the free region, $f(\text{area})$ is the whole monitoring area of the sensor network, and $r_i(p)$ is the reliability utility:

$$r_i(p) = r_i(p_i, p_{-i}) = Nbr_i - 1/D_i,$$

where $Nbr_i(p_i)$ is the number of node i's neighbors within transmission power p_i, and D_i is the probability of dropping packets. This model is applied over Dynamic Source Routing (DSR) protocol [116] and named as DSR-G. Results show that after applying game theory the selfish nodes have less impact in DSR-G than DSR.

In [117], Heterogeneous Balanced Data Routing (HDBR) is presented. It is a game theoretical distributed algorithm aiming to construct energy balanced routing trees in heterogeneous WSNs. It considers Stackelberg model [59] for the game. In this model, nodes with parent role are leaders of the game and nodes with child role are followers. Utility functions use local information of nodes. Parents have cooperative behavior, while children have selfish behavior trying to gain more individual utility. Leaders make decisions before followers, since they can predict followers' decisions. The behavior of the parents influences the behavior of the children, so that even with selfish actions of children as followers, they still contribute to the global benefit of the game (i.e., constructing a balanced tree for the entire network). Parents also try to decrease the load of other adjacent parents which are two hop away nodes at the same level. HDBR not only considers the amount of data each node has to transmit, but also bandwidth and delay as a balancing criteria. HBDR outperforms the cumulative algorithm, proposed in [118], in prolonging the lifetime of WSNs. However, such a proposal still need to be compared with other protocols in order to make a more accurate evaluation.

A Sub-Game Energy Aware Routing (SGEAR) is presented in [119]. The scheme is based on the fact that the optimization problem of routing could be mapped into a dynamic game problem, and thus, could be solved using Backward Induction method [59]. SGEAR takes the residual energy of the nodes and the energy consumption of the path into consideration. Compared with energy-aware routing, SGEAR can provide stable routes and optimize energy consumption of the whole network. Moreover, the algorithm could be combined with scheduling based scheme for prolonging the lifetime of WSNs.

Cooperative Games

In [120], a data transfer strategy is proposed to reduce the energy consumption of a WSN by forming coalitions. The idea is to consider "the proportion of sent data and the proportion of forwarded data". The coalitions are formed based on a Markov process. The concept of absorption coefficient is proposed to measure the coalitional profiles. Then, the Shapley value is used to share the coalitions' payoff. NE is used here to determine the coalitions' approximate data transfer strategies of the formed coalitions. However, finding the exact NE in this proposal is a NP problem. Thus, a genetic algorithm is given to approximate the problem. Finally, the energy consumption of nodes both when they work alone and when they cooperate is compared. Simulation results show that nodes consume less energy when they cooperate.

Cooperation Enforcement Games

A self-learning repeated-game for cooperation enforcement between randomly deployed nodes with local information only is proposed in [121]. This framework is applied in cases when nodes may not know how to cooperate even if they are willing to do so. The node's utility is quantified as its own packet transmission efficiency, which is defined as the ratio of the power spent in successful transmission of self-generated traffic over the total power required for self-generated traffic and packets forwarding. The goal of the node is to maximize the long-term average efficiency. The stage utility function for node i can be represented as:

$$U^{(i)}(a_i, a_{-i}) = \frac{P^{(i)}_{\mathrm{s,good}}}{P^{(i)}_s + P^{(i)}_f},$$

where a_i is node i's packet forwarding probability, a_{-i} is other nodes' forwarding probability, $P_{\mathrm{s,good}}$ is the power consumed in successful transmission of node i own packets to its destination, P_f is the power consumed in forwarding other nodes' packets, and P_s is the power consumed in transmitting node i own packets. In this game, nodes/players do not know when the game ends (i.e., an infinitely repeated game). Unlike one-shot games, a repeated game allows a strategy to be related to the past moves and results in reputation and retribution effects. Therefore, any cooperative equilibrium that is more efficient than NE of the one-shot game can be sustained, and any deviation causes a punishment from other nodes in future. The second step utilizes a learning algorithm to achieve the desired efficient cooperative equilibrium. The two proposed steps are applied iteratively until no more efficient cooperation point can be achieved. The proposed game is able to enforce cooperation among selfish nodes. Nodes will not have incentive to lie because lying nodes will be detected using a majority voting scheme.

In [122], the source/forwarder problem is formulated as a dynamic Bayesian game with incomplete information. This game is played by every node participating in the packet delivery, helping nodes to decide energy-aware paths toward a sink. The factors, such as energy, location (related to mobility), and cooperation between sensors, are taken into account in this work. In addition, each sensor is unaware of the energy state of its neighboring sensors. The update system is based on Bayesian game theory. It improves the efficiency of path selections and minimizes the need of instantaneous updates about local sensors' energy.

A two-player Bayesian game is modeled. One player is a sensor node, denoted by i (a source). The other player is a one-hop neighbor j of the source i. In Fig. 3.3.1, N represents an entity the decides j's type. Source i with a belief B_0 that forwarder j's energy level is sufficient has two pure strategies: forwarding H packets, or discarding the packets and remain in idle mode. The work proves that the strategy combination (i plays "sleep mode" if j is energy constrained but plays "send H packets" if j has sufficient energy, j plays "not forward", when B_0 is low) is a pure BNE strategy. In contrast, when B_0 is high, a mixed strategy approach is presented to analyze BNE. The cooperation of the forwarder j (i.e., playing "forward" or "not forward") is decided according to its payoff. Cooperation between the sensors can not be taken for granted, thereby cooperation enforcement represented by a credit-based incentive mechanism is defined in the game. A sensor will earn a reward R if it forwards a packet for a neighboring sensor, where $R > 0$. All the mathematical formulations of j's payoff in the the six different cases, illustrated in Fig. 3.3.1, are further described in [122]. Simulation results show that the game theory approach enhances network lifetime, compared to the techniques such as Flood and AODV [123], by selecting delivery paths based on a sensor's energy. The proposed work has the lowest remaining energy distribution since it has the longest operation time due to the distribution of traffic loads/energy cost among different nodes.

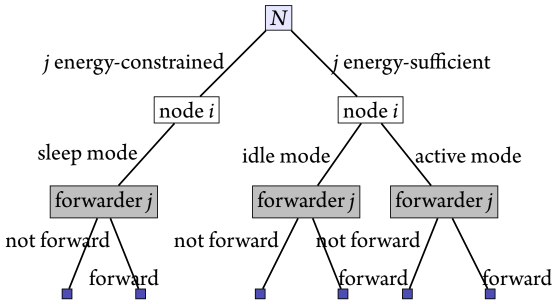


Figure 3.3.1: Extensive form of Bayesian game.

Table 3.3.1: Proposals in WSN Routing (Section 3.3.1).

Article	Year	Algorithm	Game Class	Game Techniques	Method of Energy Savings
[108]	2007	GTEBR	Non-cooperative	mixed strategy NE	helping nodes to make decisions whether to take part in the routes according to their residual energy
[110]	2009	VGTR	Non-cooperative	mixed strategy NE, action results awareness	an energy efficient of Data Routing Tree (DRT) construction, minimize network segmentation, rotate the selection of a node's next hop
[115]	2010	DSR-G	Non-cooperative	ordinal potential game	choosing reliable routes that prolong network lifetime
[117]	2011	HDBR	Non-cooperative	Stackelberg model, local information	constructing energy balanced routing trees
[119]	2012	SGEAR	Non-cooperative	dynamic game, backward induction	taking the residual energy of nodes and the energy consumption of paths into consideration
[120]	2011	-	Cooperative	coalition, absorption coefficient, Shapley value	considering the proportion of sent data and the proportion of forwarded data when making decisions
[121]	2008	-	Cooperation Enforcement	infinite repeated game, incentive mechanism (reputation-based)	packets transmission efficiency is taken into account when a node decide whether to forward packets or not.
[122]	2009	-	Cooperation Enforcement	dynamic Bayesian game, incomplete info, incentive mechanism (credit-based), extensive form, pure and mixed BNE	helping nodes to decide energy-aware paths

Discussion and Future Directions

Most of the work proposed for this domain focuses on the following problems: i) constructing or determining the energy aware paths, ii) helping nodes in making decisions weather to take a part in routes or not (selfishness problem arises here), or iii) handling selfish nodes, in order to achieve a fair residual energy distribution which prolongs network lifetime. The proposals differ from each others in the game class used, or the solution proposed. For instance, GTEBR [108] takes the residual energy of nodes as a main metric, while in [122], three factors are taken into account: energy, location, and cooperation between sensors. DSR-G [115] chooses reliable routes to prolong network lifetime. The utility function of DSR-G considers four factors: collision, transmission power, reliability, and connectivity. In HDBR [117] the amount of data, bandwidth and delay are also considered as balancing criteria. In contrast, the energy in VGTR [110] is expressed using a time derivative that represents the amount of remaining lifetime for a node based on its past workload. The reason is that the amount of remaining energy does not always convey a practical meaning, as the value of energy is dependent on additional factors. In VGTR, the selection of a next hop is rotated to achieve energy balanced routing. It is worth mentioning that [122] considers WSNs' scenarios that allow mobility, though it has a low remaining energy distribution.

In [117, 122], nodes depend on local information only, which reduces overhead. Both [121] and [122] use cooperation enforcement mechanisms to encourage a node's neighbor to forward its packets by employing a punishment and reputation-based scheme [121] or by giving rewards (i.e., a credit-based system) [122]. It is worth noting that the usage of incentive mechanisms is very useful in this domain.

Computational intelligence is used in [120, 121] to reach a desired equilibrium with reduced complexity. Again, the usage of non-cooperative games outperforms other classes of games due to its simplicity and reduced overhead.

Received signal strength (link quality) is an important metric when identifying the best possible routes. Adding this metric to the cost function should be considered in future design. Furthermore, although HDBR handles heterogeneous WSNs scenarios, the work in this direction still needs more efforts in order to study how the existence heterogeneous nodes affects the routing decisions and the overall performance of the WSN. Game theory has been also used to address energy savings in data aggregation based routing protocols which will be discussed later, in Section 3.5.1.

3.3.2 Clustering

Cluster formation is one of the early proposed methods for energy efficient operation in WSNs. It limits the scope of inter-clusters interactions to CHs and avoids redundant exchange of messages among nodes, while reducing the size of the routing table stored at each individual node. The CH selection process has a significant effect on the WSN performance. However, since it is a NP-hard problem, many heuristic methods, like LEACH, TEEN [124] and APTEEN [125], have been proposed to solve it. Those methods basically focus on balancing the energy consumption of nodes by dynamically changing the CHs. However, they do not always guarantee an energy efficient operation during the whole lifetime of network. In fact, the most commonly used clustering schemes that are based on LEACH, are usually quite inefficient from network lifetime maximization point of view. That is because if any member inside a cluster dies, this typically should not affect the lifetime of the cluster, since it does not influence the transmission of other nodes [126]. Moreover, LEACH requires all clusters to perform direct transmission to the sink. Solutions proposed for multi-hop flat WSNs are not always feasible in cluster-based WSNs.

Different Computational Intelligence (CI) approaches have also been proposed for energy aware cluster-based WSNs. Most of those approaches has been classified and discussed in [106]. Energy hole avoidance problem is also a crucial routing and clustering problem [127, 128]. This problem appears when nodes close to the sink have to transmit more packets than others, as it depletes their batteries first, hence leaving a hole near the sink and partitioning the whole network. Uneven clustering is one of the methods proposed for load balancing in order to avoid such a situation. In this method, a smaller cluster radius near the sink and a larger cluster radius away from the sink are defined, respectively.

Game theory is a suitable mathematical tool for optimizing energy efficiency in clustering problems in WSNs due to the various and distributed models it offers. In the following subsections, we present and discuss the latest proposals that use game theory in this domain. The proposals are further summarized in Table 3.3.2.

Non-cooperative Games

A Density-based Energy efficient Game-theoretic Routing Algorithm (DEGRA) is presented in [129] for solving the conflict between an individual node and the entire network. The goal is to improve the CH selection process. DEGRA sets a utility function to determine the CH based on the density of nodes. The proposal takes both the residual energy of a node and the average energy consumption of its neighbors into consideration. The CH selection problem is regarded as a k-stage dynamic game. Every player knows the utilities and strategies available to other players and each chooses its strategy based on the observation of previous stages. Thus, the game is a finite complete and perfect information game. It has a pure strategy NE (i.e., every player is playing a best response to the strategy choices of its opponents) in each stage. Besides, all stages constitute a subgame perfect NE of the dynamic game. Simulation results show that DEGRA consumes less energy than LEACH due to the effective determination and distribution of CHs.

Game Theoretic Clustering (GTC) [130] is an energy-aware distributed algorithm proposed to adaptively determine a suitable cluster size by tuning the width of nodes' regions. GTC consists of two parts: a load balancing algorithm, called LBA, and a cluster formation using a Win-Stay, Lose-Shift (WSLS) strategy. WSLS is based on the principle that if the most recent payoff is high, the same choice will be repeated, otherwise the choice will be changed [131]. Using WSLS, nodes at different locations can adapt their transmission ranges for "cluster-formation-announcement" rather than fixed ranges set at the beginning. Regions closer to the sink have smaller width, thus CHs at different hop distances could achieve similar energy consumption levels. Simulation results show that the network lifetime is extended when WSLS is adopted specially when nodes density is high. This is because that the CH role can be rotated among more nodes. The weakness of GTC is that it assumes there is only one CH in each region which limits its applicability.

To achieve energy fairness, the transmission load should be distributed among sensors such that, regardless of sensors' load conditions, no sensor node should be unfairly overburdened. In [132], the transmission load assignment in WSNs is modeled as a game. This work focuses on cluster-based and surveillance-oriented WSNs. In fact, one report from a sensor in the cluster is enough to trigger the response of the surveillance system, and the other nodes can conserve their energy by just keeping silent. The key motivation of this work is to determine which sensor is going to report to the sink. The problem can be more complicated when it considers the heterogeneity of sensors. NE of the energy balancing game is derived and it meets the QoS requirements.

Cooperative Games

To balance energy consumption of nodes and maximize network lifetime, a cooperative game theoretic model for clustering algorithms is proposed in [133]. The selfish behavior of nodes in non-cooperative games expedites network partition and results in an unfair residual energy distribution. Thus, this algorithm poses conditions for forming coalitions, considering the residual energy, transmission distance, and the number of nodes in a cluster. Nodes have to trade-off both individual cost and network-wide cost. Therefore, a cost sharing game is considered. Shapley value is chosen as a solution that assigns a single cost allocation to the cost sharing game. Compared with other algorithms, this clustering scheme prolongs network lifetime, reduces transmission time, and regulates the area of clusters to achieve energy efficiency.

In [126], a fair resource management for WSNs with a clustering scheme based on a bargaining game is proposed. The proposal assumes that every cluster has the same number of members. The NBS is applied by modeling the utility of cluster members based on their lifetime. The lifetime of a cluster member i, allocated to a time slot n to communicate with its CH at a transmission rate, $r_i(n)$ can be derived as follows:

$$\tau_i(n) = \frac{E_i}{p_i(n)} = \frac{|h_{ii}(n)|^2}{I_i(n)(2^{r_i(n)/W_i(n)} - 1)},$$

where E is the total battery energy, $p_i(n)$ is the transmission power of a cluster member i, $\tau_i(n)$ is its lifetime, which depends on the power strategy of i in a time slot n, $W_i(n)$ is the bandwidth, $h_{ii}(n)$ is the channel gain of a link from i to its CH which belongs to cluster i, and $I_i(n)$ is the total interference and noise power at the CH, which belongs to cluster i during slot n. It is proved that the set of the achievable utilities of NBS is a convex set. An optimal point can be found and the NBS is unique. The algorithm is centralized and it is valid only for single-hop transmission schemes.

A Cost Sharing Game-based Clustering (CSGC) [134] is a cooperative game that is used to solve the CH selection process. The paper presents a bi-directional cooperative clustering model, where cluster members cooperate in inter-cluster and intra-cluster transmissions. Similar to [133], a cost sharing game-based CH selection scheme is proposed to achieve an efficient management of clusters. For the purpose of simplicity and reducing the burden on CHs, the cost that CHs share does not contain the data transmission cost. CHs share only the cost of common affairs among other CHs (i.e., broadcasting information, launching cluster, synchronization, among others). A fair cost allocation is obtained through the use of Shapley value. CHs that join cost sharing are robust in term of both residual energy and position. Besides, in case of dynamic clustering, CSGC can adapt the CH selection process to the changing constraints like the node position and the residual energy. Results show that CSGC outperforms LEACH on network lifetime, transmission capacity, and energy efficiency.

In [135], a scheme that employs a small number of nodes with computing power and large batteries, called "representatives", to optimize the coalition formation problem under controllable QoS constraints is proposed. The representatives may act either as local sinks, or as coordinators of operations performed either by sensors or by coalitions. The number and density distribution of representatives critically affect the overall network design. The spatial correlation of the data gathered is also exploited to formulate a cooperation scheme that reduces drastically the number of transmissions to save energy. The WSN lifetime maximization problem is accordingly transformed into a coalition formation game of three phases initialization, optimization, and steady-state phase. In order to save energy during the initialization phase, nodes interact only with their neighbors. The optimization of the initial coalition formation is accomplished by the representatives. The proposed coalition formation satisfies Shapley axioms, and the fairness in each coalition is guaranteed. Nodes belong to different coalitions generally have different coalitional values. The performance of this scheme is examined and compared to other clustering schemes. Results show that it prolongs the lifetime of WSNs. The lifetime could be further extended by increasing the number of representatives. However, as the number of representatives increases, over partitioning will occur more frequently, reducing the aggregate benefit from coalition formation.

Cooperation Enforcement Games

The CH selection process is based on electing the node with the highest remaining energy within a cluster. The problem appears when there exist selfish nodes which lie about their remaining energy to avoid being elected. A solution based on an auction mechanism is proposed in [136]. It works as follows: Firstly, nodes with the highest remaining energy is always elected as CHs. Secondly, the mechanism encourages selfish nodes to behave honestly by providing incentives. Therefore, truth-telling is always a dominant strategy of nodes. The mechanism is derived from (Quality Assignment Vickrey-Groves-Clarke) QA-VCG [137] -an efficient multi-attributes procurement combinatorial auction model. The proposal can effectively prolong the overall network lifetime. Moreover, it can be used in Intrusion Detection System (IDS).

Auction-based Adaptive Sensor Activation (AASA) [138] is an energy efficient algorithm for target tracking in WSNs. The cluster formation process consists of a prediction method and an auction mechanism. The auction mechanism is introduced in the cluster formation process to reduce energy. The CH predicts the next location of the target and activate the nodes in the Predicted Region (PR). The rest of nodes remain in sleeping mode. Then, the CH acts as the auctioneer and the nodes in PR act as bidders. Each bidder evaluates the received task and responds the CH with a bid. The CH ranks the bids and choose appropriate sensor nodes for tracking. The node with the biggest bid is selected as the next CH, and other appropriate nodes are chosen to be the members of the next cluster. In this work, the auction mechanism is performed only when the distance between the next predicted location and the previous predicted one is larger than a certain threshold. An improved algorithm is proposed to estimate the location of a target. The target detection error is taken into account. Adaptive sensor activation algorithm is proposed to make a trade-off between

Table 3.3.2: Proposals in WSN Clustering (Section 3.3.2).

Article	Year	Algorithm	Game Class	Game Techniques	Method of Energy Savings
[129]	2012	DEGRA	Non-cooperative	NE, best response, perfect info, pure strategy, dynamic game	taking the residual energy and average energy consumption of neighbors into consideration in the CH selection process
[130]	2012	GTC	Non-cooperative	win-stay, lose-shift	an energy efficient cluster size determination
[132]	2012	-	Non-cooperative	NE	a fair transmission load assignment between cluster members
[133]	2010	-	Cooperative	coalition, Shapley value, cost-sharing game	the residual energy and the transmission distance are taken into consideration when forming coalitions
[126]	2012	-	Cooperative	NBS	a fair resource allocation between clusters by modeling the utility of cluster members as their lifetime
[134]	2012	CSGC	Cooperative	coalition, Shapley value, cost sharing game	the CHs share only the cost of common affairs among CHs in inter-cluster transmission
[135]	2013	-	Cooperative	Coalitions, Shapley axioms	optimizing the coalition formation under controllable QoS constraints, and exploiting the correlated data
[136]	2011	-	Cooperation Enforcement	Auction mechanism, incentive	electing the node with the most energy remaining as a CH, and encouraging selfish nodes to behave honestly by providing incentives
[138]	2013	AASA	Cooperation Enforcement	Auction mechanism	the CH activates only the nodes in the predicted region of the target, while the rest of nodes remain in sleeping mode, then an auction mechanism is used in the election of CH to reduce energy

energy efficiency and tracking quality. The relation between both factors is illustrated by simulation results. Moreover, when the quality of tracking is high, the number of detecting nodes is reduced to save energy, otherwise the number is increased to avoid missing a target. This is achieved by dynamically adjusting the radius of PR and the number of cluster's members according to current tracking quality. AASA achieves energy efficient performance and prolongs network lifetime.

Discussion and Future Directions

Most of the proposals in this domain are proposed for finding an energy efficient solution for one of the following clustering problems: i) the CH selection [129, 134, 136], ii) the cluster sizing [130], and iii) transmission power load balancing (fair residual energy distribution) between cluster members [126, 132, 133].

DEGRA [129] takes both the residual energy of a node and the average energy consumption of its neighbors into consideration. However, DEGRA losses efficiency when the number of members within a cluster increases. An auction mechanism is proposed in [138] for the cluster formation process in order to reduce energy. The CH predicts the next location of the target and activates nodes in the predicted region, while the rest of nodes remain in sleeping mode. In [136], the proposed mechanism encourages selfish nodes to behave honestly by providing incentives in the CH selection process. The algorithm proposed in [126] is centralized, and it is not recommended for multi-hop transmissions. The contribution of CSGC [134] is that it presents a bidirectional cooperative clustering model, where cluster members cooperate in inter-cluster and intra-cluster transmissions. Overall, we can clearly notice that the nature of cluster-based WSNs is more suitable to be solved using cooperative games, due to the similarity between coalitions and clusters formulation.

In future, specifying which nodes should be placed in the same cluster is a problem that could be addressed using game theory. Moreover, the energy holes avoidance problem has been covered only by [130] using a distributed non-cooperative game. Therefore, more efforts are still needed in such an important problem.

3.4 Coverage and Topology Control

3.4.1 Coverage

The coverage control problem is defined by answering a fundamental question: "how well do the sensors observe the physical space?". This problem has been previously formulated in several ways. The investigation of coverage problems in WSNs is conducted in [139, 140].

In general, there exists a strong relationship between coverage and lifetime in WSNs. Unfortunately, improving one of these metrics comes at the expense of the other. A strategy that is commonly employed to achieve a trade-off between those conflicting goals is to schedule only few nodes to be awake at any given point of time. This way the network lifetime is extended without compromising the coverage requirements. Therefore, the key challenge here is to design those scheduling algorithms based only on local information, aiming to achieve near optimal performance.

The set *k-cover* algorithm is an energy efficient coverage solution, whose goal is to determine whether every point in the service area is covered by at least k sensors subject to lifetime requirements. However, the existing set *k-cover* algorithms [141–143] are centralized, and can not adapt to large-scale sensor network applications. Moreover, in [142, 143] it is proved that this problem is an NP-complete problem. There are some heuristic algorithms in the literature to find the cover sets. For example, [144] proposes a polynomial-time algorithm in terms of the number of sensors. The algorithm can be easily transformed into distributed protocols. *Worst and best case coverage* are also a well-known problem which is discussed in [139]. In [145], an efficient distributed algorithm to find an optimum best-coverage-path with the least energy consumption is presented.

The use of game theory could be helpful for tackling this challenging problem, and in finding efficient and distributed solutions. Table 3.4.1 lists the latest work that use game theory in this domain. The considered proposals are discussed in the following subsections.

Non-cooperative Games

In [146], the Distributed, Robust and Asynchronous Coverage (DRACo) algorithm is presented. Its goal is to solve the set *k-cover* problem in order to provide the maximum possible coverage subject to lifetime constraints. It is assumed that $N = |\mathcal{N}|$ nodes are randomly scattered in a field of area A with sensing and communicating range R_s and R_c, respectively. Every node belongs to one of k disjoint sets. Time is slotted and most of energy is consumed during the active slots. Nodes are scheduled to be active over a schedule of length i, such that in each slot i, nodes belonging to set k are active. Therefore, the lifetime of the network is proportional to k. Given such a schedule, the objective is to determine the optimal k partition of $\mathcal{N}$, such that the average coverage is maximized. The optimization problem is formed as follows:

$$\max \;\; C(s) = \frac{1}{k} \sum_{i=1}^{N} C_i(s),$$

$$\text{s.t. } s \in \mathcal{S},$$

where $\mathcal{S} = \{s_1, s_2, \ldots s_N\}$ represents a partition of $\mathcal{N}$ into k cover sets (i.e., $\mathcal{S}$ is the set of all possible *k-covers*). $C(s)$ is the coverage metric which depends on the topology of the network, the sensing range R_s of the nodes, and on k. A key challenge is to achieve this partition in a distributed manner with local information only and yet provide near optimal coverage. For a node i, which has chosen a slot s_i, if all of its sensing region is covered by another nodes, then node i is redundant in that slot. Therefore, if node i switches to a slot where there exists a region covered only by itself, the coverage performance would be improved (see an example in Fig. 3.4.1). The concept called "the

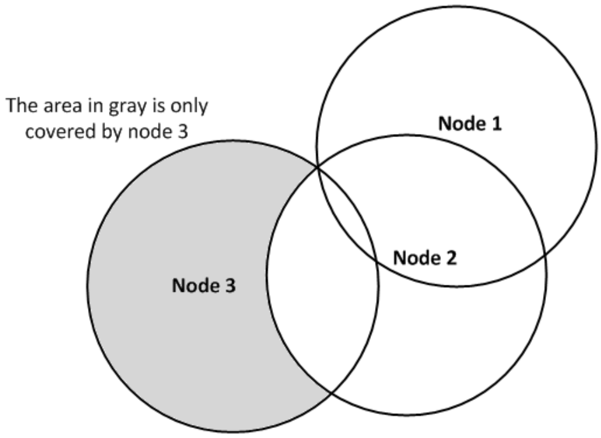


Figure 3.4.1: The strategy of node 3 is the area in gray.

regret of a node", defined in graphical games [147], is used. The game converges to NE in a purely distributed way. Moreover, DRACo is robust to network dynamics and can converge even when executed asynchronously. The simulations indicate that the convergence speed of DRACo is almost constant with the number of nodes N and k.

The work done in [148] is an extension of [146]. It proposes synchronous and asynchronous algorithms, which converge to a pure strategy NE. Moreover, it analyzes the optimality and complexity of the pure NE in the coverage game via the price of anarchy [20]. It is proved that, the ratio between the optimal coverage and the worst case NE coverage, is upper bounded and depends on the maximum number of nodes which cover any point in the NE solution. It is also proved that finding a pure strategy NE in the general coverage game is PLS-complete. Simulation results show that the NE coverage performance is very close to the optimal coverage and the convergence speed is sub-linear. Even under a noisy environment, the algorithms can still converge to a NE point.

In [149], [146] is further extended, addressing the same problem by proposing a distributed algorithm. In [148], the maximum coverage set algorithm is proposed. Thus, [149] utilizes the maximum coverage set as an upper limit of the coverage set division. On the basis of this maximum, it takes the node Minimum Layer Overlapping Subfields (MLOF), satisfying division conditions, as a node's utility function. Then, it puts forward a distributed heuristic algorithm to get optimal strategy by iteration in order to reach NE. Using game theory, the network lifetime is maximized while ensuring the maximum area coverage. However, if the destiny of nodes is high, increasing the node coverage set will lead to an increased number of iterations.

In [150], the Game-theoretical Complete Coverage approach (GCC) is proposed to ensure a complete network coverage through adjusting the coverage range of nodes and controlling the redundancy in network coverage. The work takes into account the transmission power control. The motivation of the work is that in a network that has changed its topology due to mobile or sleeping nodes, parts of nodes' coverage area should be decided again. In this case, every node probably has to update its operating parameters. In many cases, the way to solve this problem is through a detailed planning of the network topology by optimizing the coverage area of every node. This approach is easy to manage but not suitable for the stability of WSNs whose topology changes fast. The aim of GCC is to avoid the series of holes in coverage rapidly and effectively. Game theory is used to optimize this problem and the payoff of every node is defined as follows:

$$\text{Payoff}=1 - ar_i^2 + \beta p_i,$$

where the value of the complete coverage is 1, r_i is the inductive radius of node i, and a is a parameter that ranges between 0 and 1. It affects the amount of energy consumption. Smaller coverage area saves more energy. β is a parameter (also between 0 and 1) related to the importance of the coverage level that should be considered when a node's decision is made, and p_i is the coverage level. The strategy of power management is that in each stage of the game, the sink broadcasts energy level data. Then, an energy level, determined through NE, is confirmed. If any node deviates, other nodes will increase their energy levels in order to punish it. All nodes know other nodes energy conditions. In every stage of the game, the energy distribution of every node achieves NE. During the whole repeated game processes, a certain equilibrium is reached, which is more effective than the one-shot NE. However, this proposal is not fully distributed since the sink plays an essential role.

Game-theoretical Total Link (GTL) [151] is an algorithm based on game theory designed for optimizing the transmission range dynamically in order to save energy. An amount of 20% of energy is saved in comparison to the Critical Transmitting Range (CTR) algorithm [152], where sensors assign fixed and equal transmission ranges, which results in a coverage overlapping problem (i.e., energy waste). Nodes control their energy consumption flexibly according to topology changes without loss of connectivity and robustness. For doing so, the following payoff function of a node is used:

$$\pi_i = 1 - ar + \beta(n-k),$$

where r is the transmission range radius, α and β are weighting parameters, n is the amount of neighbors, and k is the neighbor expectation. $\beta(n-k)$ is the benefit from neighbors, and $-\alpha r$ represents the energy consumption. Through repeated games, the whole network will reach NE which means that most nodes will decrease their energy consumption. Results show that with a sleeping strategy, sleeping nodes would waste more energy than active nodes.

The work presented in [153] formulates the coverage optimization problem for mobile sensors as a constrained repeated multi-player strategic game. Each sensor tries to optimize its own coverage while minimizing the processing energy cost. A number of learning rules (e.g., best response dynamics and adaptive play) have been proposed to reach NE. Utility values induced by alternative actions are inaccessible because of the information constraints caused by unknown rewards, motion, and sensing limitations. To tackle this challenge, two distributed payoff-based learning algorithms are developed, where each sensor remembers only its own utility values and actions played during the last two rounds. These algorithms are proven to be convergent to the set of constrained NE and global optimum of a certain coverage performance metric. The utility function proposed for an agent i that aims to capture the sensing/processing trade-off is:

$$u_i(s) = \sum_{q \in D(a_i, c_i) \cap Q} \frac{W_q}{n_q(s)} - f_i(c_i).$$

The first term of the formula represents the benefit that agent i obtains through sensing. The second term represents the sensing energy/processing cost. This coverage game is proved to be a constrained EPG. More results of this work are presented in [154, 155].

Cooperative Games

In [156], a compromise model based on a cooperative game for both energy conservation and sensing accuracy is proposed. A sensing model which allows a flexibility in optimizing networks' sensing activity is presented. The interaction between sensor nodes is modeled as a cooperative bargaining game, where individual sensors cooperate for achieving the application sensing requirements while minimizing and balancing the energy consumption. Kalai-Smordinsky Bargaining Solution (KSBS) is used to find a distribution rule that optimizes the trade-off in this problem. Simulation results show that the network lifetime is extended, compared to a linear programming and a heuristic methods.

Table 3.4.1: Proposals in WSN Coverage (Section 3.4.1).

Article	Year	Game Class	Distributed/Centralized	Game Techniques	Method of Energy Savings
[146]	2007	Non-cooperative/Cooperative	Distributed	NE, regret strategy	maximizing the area coverage subject to a lifetime guarantee
[148]	2008	Non-cooperative	Distributed	NE	maximizing the area coverage subject to a lifetime guarantee
[149]	2009	Non-cooperative	Distributed	NE, repeated game	maximizing the area coverage subject to a lifetime guarantee
[150]	2008	Non-cooperative/Cooperative	Centralized	NE, repeated game	adjusting the coverage range of nodes while controlling the transmission power
[151]	2009	Non-cooperative	Distributed	repeated game	optimizing the transmission range dynamically in order to save energy
[153]	2013	Non-cooperative	Distributed	best response, exact potential game, repeated game	optimizing the area coverage while minimizing energy costs
[156]	2010	Cooperative	Distributed	Kalai-Smordinsky bargaining solution	a compromise model for both energy conservation and sensing accuracy
[157]	2013	Cooperation Enforcement	Distributed	repeated game, incomplete info, incentive mechanism (reputation-based)	optimizing the network coverage taking the energy efficiency and the selfish behavior into account

Cooperation Enforcement Games

In [157], a Coverage Maintenance Protocol (CMP) that is based on game theory is presented. An incentive mechanism is used to tackle the selfish behavior of nodes. Selfish nodes may refuse to wakeup to execute a Coverage Eligibility Rule (CER) (i.e., to find the eligibility of a sensor node to sleep) for one or several rounds, in order to save more energy and increase their lifetime. The objectives of this work are to detect and prevent such behavior, and to optimize the network coverage. In addition, CMP assures that the network coverage degree is maintained by the remaining active nodes. Thus, it helps to balance the energy consumption by scheduling the active state of nodes. The problem is formulated as a multi-stage repeated game, since the phases of coverage optimization and maintenance consists of several rounds. The sent and received control packets overhead is evaluated according to the number of detected selfish nodes. Results show that the energy efficiency and the network lifetime are affected when the number of selfish nodes increases. Results also reveal a trade-off between coverage range (i.e., accuracy of selfish node detection) and the control packet overhead, as it affects energy efficiency.

Discussion and Future Directions

Designing a distributed energy-saving solution in this domain is a challenge that has attracted researchers' attention. All the previous set *k-cover* algorithms are centralized. Besides, it can not adapt to large-scale sensor network applications. In [146, 148, 149], game theory has been applied to address the *k-cover* problem in order to provide the maximum possible coverage subject to a lifetime guarantee. However, the algorithm in [146, 148] has many limitations as discussed in [149]. Firstly, the network lifetime is related to the number of coverage node sets. Secondly, the algorithm aims at maximizing network lifetime at the expense of overall coverage. This is against users demands in real monitoring applications, when it is required to enlarge the coverage area as far as possible. Thirdly, the algorithm can not achieve a balance between network node density and the number of coverage sets number to optimize the network coverage area. Finally, this algorithm uses node's exposed area as a payment function, which makes calculations in the real application complicated and less accurate. In [149], when node destiny is high, increasing the node coverage set number will lead to an increase of algorithm iterations.

Coverage control for mobile WSNs is addressed in GCC [150] and [153]. GCC allows nodes to adjust their coverage range by taking transmission power control into account. The main drawbacks of GCC are that all nodes should know other nodes' energy levels. Moreover, the sink plays an essential role by broadcasting energy level data. In contrast, in [153] the utility values induced by alternative actions are inaccessible because of the information constraints. Besides, it employs an accurate sensing model. GTL[151] optimizes transmission ranges dynamically to reduce coverage overlaps in order to save energy.

On the other hand, cooperative games are not widely used in this domain. Only one proposal in the recent literature uses a cooperative game to address the trade-off problem between sensing accuracy and lifetime by using scheduling techniques in [156]. Finally, cooperation enforcement games are very useful when some nodes might have a selfish behavior or deviate from NE (see [157]).

In future work, the collaborative relation between the coverage control and the MAC layer (e.g., scheduling nodes to sleep according to the required coverage) will be an important issue that could be modeled using game theory. Moreover, game theory could also be used to address the joint coverage and power control problems. For example, the presence of multiple wireless networks in ISM bands, including Wireless Local Area Networks (WLANs) and other WSNs, is a cause of mutual interference. WSNs may use dynamic channel hoping to avoid interference from external networks by moving all or one part of the network to a different channel [158]. To do that, all sensors should agree on that decision as the network connectivity must be guaranteed.

3.4.2 Topology Control

In some WSNs applications, sensing nodes need to be placed accurately at predetermined locations. Given a geographical coverage, Topology Control (TC) determines where to place nodes, CHs (in cluster-based topologies), or sinks. It basically helps in arranging the communication among them.

The network lifetime during which the topology is preserved -or adapts dynamically- is referred to as topological lifetime. Many researchers aimed to maximize this topological lifetime with regard to a given mission and a certain amount of initial energy. One energy savings strategy is to allow each node to adjust its transmission power to cover only a specific set of direct neighbors, while preserving connectivity and coverage. A survey on distributed TC techniques for prolonging the lifetime of WSNs is provided in [159]. However, the failure of nodes due to energy depletion may partition the network leaving some areas uncovered. Moreover, it has a negative effect on the application since it prevents data exchange. Therefore, topology management techniques for tolerating node failures in WSNs have been surveyed in [160].

Since topology may vary with time due to malfunctioning nodes or node mobility, it is preferable that the network is able to dynamically adjust the topology in a distributed manner. The TC algorithms found in the literature are either centralized algorithms (i.e., require global network information), semi-distributed or distributed algorithms [159, 161]. However, a central coordination is often impractical, therefore distributed approaches are of a more importance. In this context, a simple distributed topology control algorithm that determines the minimal power consumption operating point for each node in a multi-hop wireless ad hoc network is proposed in [162]. In this algorithm, each node makes local decisions about its transmission power. The local decisions collectively guarantee global connectivity.

Game theory can effectively address the process of nodes' deployment and transmission power control in order to reach a solution which optimizes energy efficiency and prolongs network lifetime. The following subsections will discuss the latest proposals in this domain. The papers are summarized in Table 3.4.2.

Non-cooperative Games

Delta-Improvement Algorithm (DIA) [161] is a TC game that extends the Max-Improvement Algorithm (MIA) [163]. The utility function u_i of the game specifies that nodes have enough incentives to establish and maintain connectivity with a sufficient number of neighbors, and ensures that the network does not partition. It can be expressed as follows:

$$u_i(p) = \phi_i(g(p)) - X_i(p_i),$$

where ϕ_i represents the benefit (i.e., of being connected) node i derives from network g, and X_i is the cost (i.e., energy consumption). This TC game is a potential game which guarantees the existence of NE. The game also admits many locally efficient NE. However, only a subset of those NE topologies is globally efficient from an energy efficiency point of view. The problem with MIA is that, although it converges to topologies that preserve network connectivity, being greedy leads to a biased steady-state power-level distribution. In DIA, each node makes small decrements in its power level if that change improves the utility. Otherwise, the node reverts to its previous power level. At the end, the transmission power distribution is more fair. This work shows that under DIA, the induced topologies are energy efficient and preserve network connectivity. It is observed that the NE topology obtained by DIA is Pareto efficient. For any random topology, and from the Pareto efficiency and uniqueness of NE, it can be deduced that the steady-state power allocation under DIA is lifetime optimal.

In [161], an algorithm that guarantees convergence to a connected network is proposed. The algorithm requires global information flowing through the network in order to check at each iteration the connectivity of the network. [164] relaxes that assumption and proposes a fully distributed algorithm based on local information only to adjust the transmission power of each node. Hence, the network becomes connected with an energy efficient solution. The algorithm is formulated as a non-cooperative game where nodes exchange information only with their neighbors (i.e., local information only). Potential games (i.e., EPG and OPG) are used to prove the existence of NE. Results indicate that for a relatively low node density, the probability that the proposed algorithm leads to a connected network is close to one.

Power management and TC are directly correlated. The work presented in [165] is motivated by this consideration. It proposes a joint topology and power control algorithm based on game theory to analyze the decentralized interactions among heterogeneous sensors. Three desirable characteristics: reliability, connectivity, and power efficiency, are considered in the game. The strategies played by nodes reflect the trade-off between the Frame Access Rate (FSR), node degree, and power consumption. The power control problem is formulated as a realistic incomplete information dynamic game model with sequential moves. Two solution schemes for implementations are provided, NEPow and BEPow. NEPow is derived from the NE of the static game model. BEPow is derived from the BNE of the incomplete information dynamic game model. Both NE and BNE are proved under sufficient conditions. Results show that the average transmission power over all nodes is reduced by 45% compared with the case without power control.

In many game theory based TC algorithms, every node has to make other nodes aware of its actions by transmitting some control information repeatedly. This results in an unnecessary energy waste and network lifetime minimization. To solve this problem, a distributed Virtual Game-based Energy Balanced TC algorithm (VGEB) with incomplete information is proposed in [166]. In VGEB, every node needs to exchange information only once. Then, based on the obtained information, it can find out its own transmission power by executing a virtual game. This work illustrates that the TC virtual game is a potential game and can converge to NE, which is Pareto optimal. Moreover, VGEB can easily construct the topology with a low information complexity of $O(n)$, and the induced topology can maintain the network connectivity, where n is the number of nodes in network. VGEB is also compared with DIA. Results show that VGEB outperforms DIA in: i) balancing nodes' energy consumption by selecting some of the available nodes with higher energy as their direct neighbors, ii) reducing the energy wasted in information exchange, and iii) prolonging network lifetime. In addition, the average-hops and maximum-hops of the shortest path between a pair of nodes in VGEB are much shorter than in DIA. Hence, VGEB reduces end-to-end delay.

The Neighbor Selection (NS) game is presented in [167]. In this game, each individual node tries to selfishly choose its neighborhood such that its own energy consumption is optimized. The goal of nodes in this game is different in the sense that every node tries to egoistically optimize its energy consumption by connecting itself to a minimal set of neighbors while also using the minimal transmission power. The choice of a minimal neighbor set allows nodes to minimize their traffic load. This objective creates a new game with completely different outcomes than the original TC game, where nodes are only interested in minimizing their transmission power. The utility function

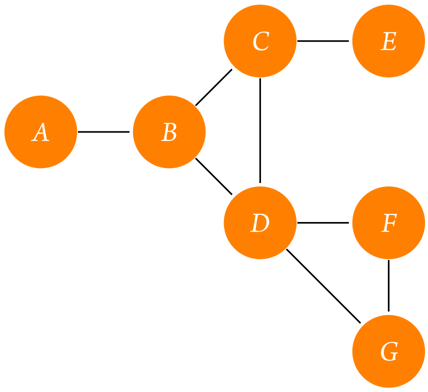


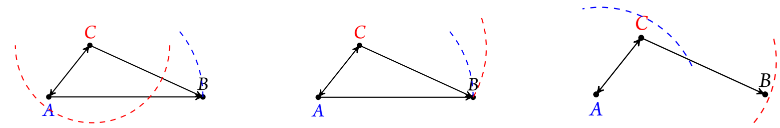
Figure 3.4.2: A sample NE topology.

of node i can be expressed as:

$$u_i(L) = Mf_i - \sum_{j,(i,j)\in E^L} v_{i,j} p_i,$$

where f_i is the number of nodes connected to node i, M is a fixed benefit multiplier. The negative term represents the energy cost, where $v_{i,j}$ is the volume of traffic going over the link (i, j), and p_i is the transmission power of node i to any of its neighbors. The multiplier M is set to a value larger than any possible energy cost value. The benefit term indicates that nodes prefer connectivity over energy savings. However, they would get more rewards by maintaining this connectivity with a lower energy usage. Hence, a connected topology is always preferred by nodes over a disconnected one. Fig. 3.4.2 illustrates a sample NE topology in which no node benefits from removing any of its non-cut links. In [167], a simplified version of this game where nodes know their transmission power before participating in the game is proposed first. Then, a couple of distributed algorithms is proposed to obtain stable topologies in a network of selfish nodes using both global and local connectivity information. The general case where the transmission power is unknown is also taken into consideration. Results show that the global method yields to about 20% higher total energy consumption than the approximated (stable) solution. However, if the local information is appropriately chosen, the local method can reduce this gap by more than 10%.

Cooperative TC with Adaptation (CTCA) [168] is a dynamic TC algorithm based on game theory that considers both energy costs across links and the amount of node's available energy. It maps the problem of maximizing the network's lifetime into an OPG. This allows a node running



(a) The initial topology where no node can reduce its transmission power.

(b) Node C sacrifices and increases its transmission power to directly connect to B.

(c) Node A can now reduce its transmission power and connects only with C.

Figure 3.4.3: An example illustrating cooperative topology control.

CTCA to make a sacrifice by increasing its transmission power dynamically if it helps in reducing the energy consumption at another node that has a shorter lifetime (see Fig. 3.4.3). The existence of NE is proved. Simulation results indicate that CTCA extends the life of a network by more than 50% compared to well-known algorithms.

Placing relay nodes is a possible solution to restore connectivity in partitioned WSNs. However, existing solutions require some global information, regarding the availability of the number of partitions, and the location of other nodes, among others, which may not be available in all applications. A distributed game theory based approach for the placement problem of relay nodes is proposed in [169], in order to guarantee network recovery for partitioned WSNs. Movement decisions of the relays are regarded as a network game. A BNE function is assigned to each partition using limited information about the routes and partition boundary nodes. A probability distribution function is defined for each partition using the estimated equilibrium function (i.e., BNE function). This game allows some relay nodes (the leaders) to determine the partition to be connected with (i.e., for recovery) based on the probability distribution function of the partitions. The recovery process proceeds with the partition with the next highest priority until the network is completely recovered (i.e., reaching system-wide NE). Results show that this approach performs slightly better than a centralized approach in terms of the distance traveled by all relay nodes between partitions, which enhances the network lifetime. However, taking the residual energy of the nodes into account when making decisions is planed for the future work.

Table 3.4.2: Proposals in WSN Topology Control (Section 3.4.2).

Article	Year	Algorithm	Game Class	Distributed/Centralized	Game Techniques	Method of Energy Savings
[161]	2008	DIA	Non-cooperative	Centralized	potential game, Pareto efficient	preserving network connectivity with a fair transmission power distribution
[161]	2009	EPG,OPG	Non-cooperative	Distributed	exact and ordinal potential game	preserving network connectivity with a fair transmission power distribution
[165]	2009	Joint TC and Power	Non-cooperative	Distributed	dynamic game, sequential move, static game, BNE, incomplete info	the transmission power control is considered in the TC procedure
[166]	2012	VGEB	Non-cooperative	Distributed	potential game, incomplete info, Pareto efficient	reducing the energy waste when exchanging the information, and selecting the nodes with higher energy as direct neighbors
[167]	2012	NS	Non-cooperative/Cooperative	Distributed/Centralized	NE, best-response	optimizing the energy consumption by connecting with a minimal set of neighbors and using the minimal transmission power
[168]	2012	CTCA	Non-cooperative	Distributed	NE, ordinal potential game	a node makes a sacrifice by increasing its transmission power dynamically if it can help their neighbors (with short lifetime) to reduce energy consumption
[169]	2014	-	Non-cooperative	Distributed	BNE	efficient placement of relay nodes to guarantee network recovery in partitioned WSNs
namvar10	2010	-	Cooperative	Distributed	coalition, non-superadditive, rewards	maximizing the feasible sleep time

Cooperative Games

Given that target localization requires nodes cooperation, the main idea of [170] is to dynamically achieve an optimal formation of collaborative coalitions. For this reason, a non-superadditive cooperative game is proposed. The term non-superadditive means that the grand coalition (i.e, the coalition comprising all nodes) is not optimal. Nodes in each coalition share measurements to localize a particular target. As a result, they are rewarded with sleep times. The paper explains why the optimal coalition does not necessarily comprise the nearest nodes to the target. In general, finding the optimal coalition structure is an NP-complete problem. This motivated the use of randomized algorithms to solve the coalition formation game. At the end, nodes autonomously decide which coalition to join, while maximizing their feasible sleep times.

Discussion and Future Directions

It can be noticed from the proposed studies that TC and coverage problems are strongly related to each other (e.g., adjusting the transmission range, and scheduling which nodes must turn on/off and when). Energy efficient game theory based TC solutions should basically take into account the connectivity of the network and the fast convergence to a NE point. Proposals like [161, 164, 167, 169] use non-cooperative games to solve this problem. Potential games are also used widely to solve this kind of problems (see [161, 164, 166, 168]) since they are easy to implement and guarantee the convergence to NE. [166, 167] reduce the unnecessary energy waste in information exchange. CTCA [168] takes into consideration both energy costs across links and the amount of nodes' available energy. A node running CTCA makes a sacrifice by increasing its transmission power dynamically if it helps in reducing the energy consumption of another node that has a shorter lifetime.

Given that the target localization requires nodes cooperation, a coalitional game is proposed in [170], which is the only cooperative game found in the literature in this domain.

To the best of our knowledge, the use of game theory in this domain usually assumes homogeneous wireless nodes. In future, addressing the connectivity and bi-directionality issues in heterogeneous WSNs should be given more attention (e.g., nodes with higher hardware capabilities can help others to execute their tasks efficiently).

3.5 Data Aggregation, Security, Task Allocation and Energy Harvesting

3.5.1 Data Aggregation

Transmitting all sensor data, specially in dense WSNs, can result in a high traffic load and cause congestion at destination nodes. This may result in higher energy consumption for the overall network. A multi-hop WSN can reduce network traffic by aggregating data on routes to the sink (see Fig. 3.5.1). This is achieved by using functions such as suppression (i.e., eliminating duplicates), min, max, and average, among others. Most routing algorithms in WSNs aim to minimize the total transmission cost of the collected data in a distributed manner. Taking into account data correlation, as well as transmission energy per bit in routing decisions, the system performance can be improved to a great extent [171].

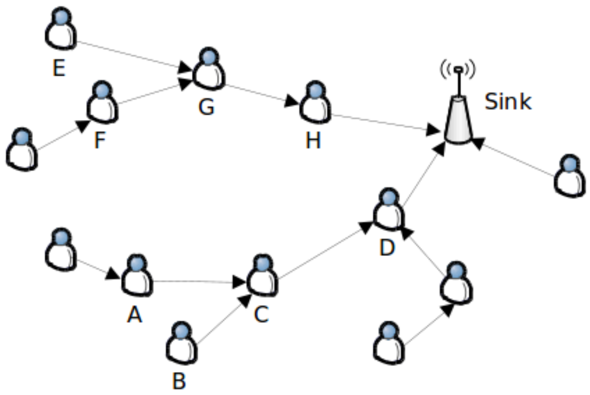


Figure 3.5.1: Node G aggregates correlated data between E, F, and sends it to H which will deliver it to the sink.

Data aggregation and in-network processing techniques strongly depend on the type of data used in each specific application. A survey of traditional data aggregation algorithms used in WSNs is presented in [172]. These techniques have been used to achieve energy efficiency and traffic optimization in a large number of routing protocols [111, 173, 174]. In [175], a structure-free data aggregation protocol (i.e., not using any structure such as tree-based or cluster-based) is proposed to reduce delay and energy spent on building and maintaining a data aggregation structure for environments where nodes may move or fail.

Game theory models are used to achieve an energy efficient data aggregation in a way that does not affect the network lifetime. The proposals are discussed below and summarized in Table 3.5.1.

Non-cooperative Games

Correlation Aware Routing (CAR) [171] is an adaptive and distributed routing algorithm based on potential games. It is proposed to address the problem of designing an energy efficient transmission structure in WSNs where all nodes aggregate correlated data over intermediate nodes on a route to the sink. The total amount of energy consumed to correctly deliver one data symbol, accounting for data redundancy through correlation, is calculated. The cost function takes into account energy consumption, interference, and correlated data. CAR is proved to be an EPG, for which a best response strategy is shown to converge to NE. The performance of CAR is compared with Minimum Energy Routing (MER) schemes and MEGA [176]. Simulation results show that

CAR outperforms both algorithms in saving the total effective energy in normal and dense networks. However, the end-to-end transmission delay minimization is not taken into consideration in this work.

Reverse Game Theory based Aggregator Node Selection and Ant Colony Optimization based Routing (RGTAGN-ACO-R) [177] is a novel framework for power efficient data aggregation in WSNs. The goal is to maximize the lifetime of the sensor network. The proposed system has two phases. In the first phase a robust and energy aware selection of aggregation nodes using reverse game theory is achieved. The second phase is associated to an optimized data dissemination and power efficient routing scheme using Ant-colony Optimization. Simulation results indicate remarkable power optimization and enhanced QoS in comparison to LEACH.

Discussion and Future Directions

This domain is strongly related to the routing domain. Game theory has been recently used in two studies in this area. In the first one, CAR [171], the cost function takes into account the energy, interference and correlated data. However, the proposal does not pay attention to the end-to-end delay. The other [177] divides the routing process into two phases, and uses game theory in the first phase for a robust and energy aware selection of aggregation nodes.

Many security challenges arises from data aggregation. This is related to the fact that thee identification information of data is lost once it is aggregated, making the detection of malicious nodes more complicated [178].

Game theory could be used in future work to address those security challenges. It should focus on the trade-off between energy balancing and delay in both structure-based and structure-free data aggregation schemes. Besides, comparisons with heuristic based data aggregation proposals [179, 180] are still not covered. Heterogeneous WSNs are suitable scenarios for data aggregation because the multiple tasks (i.e., relaying, sensing and aggregation) being assigned to nodes with limited resources, might quickly drain their battery.

3.5.2 Security

Wireless links in WSNs are susceptible to eavesdropping, impersonating, message modification, Denial of Service (DoS), among others. Due to the limited capabilities of nodes, researchers had to think about efficient approaches to solve those problems. Various security challenges and types of attacks in WSNs have been analyzed in the literature. The key issues that need to be resolved for achieving adequate security are summarized and surveyed in [181, 182].

Many secure routing protocols such as SEAD [183], Ariadne [184], SRP [185], and SAODV [186] are designed for protecting routing information. A misbehaving node could behave well during the route discovery phase, but drop data packets later. Moreover, if misbehaving nodes drop packets, all those solutions can not detect and prevent such attacks, as they focus only on the detection of modification of routing control traffic or fabricating false routing information. With WSNs, security not only has to worry about malicious nodes but also about "selfish nodes". A selfish node is a node that misbehaves, not necessarily because it is a malicious node, but because either it prefers to save its own limited resources or it may belong to a different authority. The existence of selfish nodes in a network may rapidly decrease network performance and create what is called "blind spots".

Game theory models have been widely used in this domain. A survey of security approaches based on game theory in WSNs is presented in [187]. The recent proposals for achieving energy efficient security algorithms in WSNs based on game theory are discussed below and summarized in Table 3.5.1.

Non-cooperative Games

A proactive defense scheme that uses an evolutionary game theory model is presented in[188]. In evolutionary game theory proposes, players are meant to be with bounded rationality and partial knowledge of the state of the game [189]. The scheme allows nodes to have the ability to learn the evolution of rationality by dynamically adjusting their defense strategies according to attackers' strategies. Nodes aim to find a strategy that balances their own rewards (i.e., successfully forwarding of data packets) and their costs resulted from deploying the security measures (i.e., energy consumption). The proposed game helps nodes to achieve this balance. However, nodes to consume large amounts of energy if they want to obtain and keep updating the information about the state of the entire network, in particular if the topology changes continuously.

An energy aware Trust Derivation Dilemma Game (TDDG) for WSN-based Internet of Things (IoT) networks is presented in [190]. The work aims to minimize the energy consumption, while maintaining an adequate security level in the network. First, a risk strategy model is presented to stimulate nodes' cooperation. Then, TDDG is used in the trust derivation process. Based on the mixed strategy NE, the optimal ratio between the gain and the cost and the probability of the selected strategy are discussed. Simulation results show that the proposed scheme achieves the desirable security and reduces energy consumption of the network compared with traditional flooding trust derivation mechanisms.

Coordinator selection is a technique that allows nodes to defend against attacks and reduce the data delivery delay. In [191], an adaptive coordinator selection algorithm using game and fuzzy logic is proposed. It enables the defender to proactively select a reliable coordinator to minimize the expected network energy loss. The proposed game model consists of two interrelated formulations: a stochastic game for dynamic defense and a best response policy using evolutionary game formulation for the coordinator selection. The amount of remaining battery of the selected coordinator is taken into account. Global NE exists and a mixed-strategy solution for the defender and the attacker is designed. It combines both evolutionary game NE strategies and stochastic game NE strategies in order to increase the payoff of both players.

Cooperation Enforcement Games

Trustworthy Energy Efficient Routing (TEER) [192] is an algorithm that aims to distribute energy consumption across sensors evenly, as well as to increase path security in a hierarchical-cluster sensor network. The CH election process is modeled using game theory. The NE of the game corresponds to the healthiest CHs having the highest energy and trust levels. Firstly, each node establishes a possible head set $\mathcal{P}$ which is empty at the initialization phase. Secondly, each node will broadcast its own payoff (i.e., π value) to all its neighbors. After that, each node will compare each neighbor's π value with its own value. Then, it adds the nodes whose π value is larger than its own to its possible head set $\mathcal{P}$. If a node's possible head set $\mathcal{P}$ is still empty, this node will declare itself as a CH. The payoff value is calculated using the following formula:

$$\pi_i = \alpha E_i/E_{\text{init}} + \beta R_i - \gamma \sum P_{\text{pathloss}}/(n_i P_{\max}),$$

where α, β and γ are weighting parameters of node's i residual energy level, trust level, and average path loss to its neighbors, respectively. E_{init} denotes a node's initial energy level, E_i denotes a node's current residual energy level, R_i denotes a node's trust level, and $\sum P_{\text{pathloss}}/(n_i P_{\max})$ denotes a node's average path loss to its neighbors which can provide the CH's appropriate position within a cluster. Every node tends to elect a neighboring node with a maximum π value as a CH to maximize its payoff. Following this strategy, the energy consumption is distributed and path security is increased. Results indicate that this proposal produces a longer network lifetime and a more trustful network in comparison to LEACH.

The impact of applying game theory on network throughput, battery consumption, and accuracy of selfish node detection in WSNs is investigated in [193]. A protocol that is based on game theory is presented. It allows sensors to decide whether or not to forward packets by i) defining a suitable cost and profit for routing and forwarding incoming packets, and ii) keeping a history of experiences with non-cooperating nodes in order to drive selfish nodes out of the WSN. The incentive for each node is to have a better reputation. A node that acts selfishly is the one that randomly drops packets to conserve energy or to corrupt the network intentionally. Over time, nodes with low reputation can be isolated and labeled as "selfish nodes". At each node, there is a trade-off between saving energy resources and maintaining their reputation. The proposal has two main weak points. Firstly, selfish nodes detection is done by the sink which means that the method is centralized. Secondly, it is difficult to detect selfish nodes if there is a large number of nodes with low reputation.

Game-Fuzzy Q-Learning (G-FQL) [194] combines both game theory and fuzzy Q-learning to detect Distributed Denial-of-Service (DDoS) in a cluster-based WSN. DDoS is characterized by the presence of an attacker who sends flooding messages that exhaust nodes' energy in reception and processing. Besides, flooding messages prevent nodes from entering 'sleep mode'. G-FQL is a triple-player game, in which a CH (detector) and the sink (defender) cooperate to provide defense against an attacker. The game has two phases. In the first phase, a CH (player-1) identifies the level of the attack, that depends on the disruption done by the attacker (player-2), using a fuzzy Q-Learning algorithm. For attacks detection, player-1 adopts three strategies, namely: catch, missed, and low catch. If the level of the attack is above the default value threshold, player-1 (CH) transmits an alarm event containing information about the malicious node to the sink (player-3). That information is preprocessed by the sink to travel from phase 1 to 2. In the second phase, the sink prepares a countermeasure strategy by employing the fuzzy Q-learning algorithm to confirm the malicious node's behavior (i.e., past attacks). The detection player (CH) and the defender (sink) coordinate their defense with each other. Incentive mechanism for cooperation enforcement has been applied. Two constant reward values are defined. R_1 is the gain of the IDS1 when the CH detects an attack, and R_2 is the gain of the IDS2 when the sink protects the WSN. If the CH does not identify the malicious node during the attack, the reward of the IDS1 would be $-R_1$ (a negative reward). Likewise, if the sink fails to defend the WSN during an attack, the payoff of the IDS2 would be $-R_2$. It has been determined that repeated interaction sustains cooperation, builds confidence and enhances reputation. The game has the following utility function:

$$U = \rho \, \mathrm{SP} - \beta \, \mathrm{FN} - \theta \, \mathrm{FP},$$

where ρ is the weight of the effective prediction, SP is the true confidence rate of attack patterns, β is the weight of failed estimates (i.e., attacks but no defense), FN is the false negative of attack patterns (i.e., attacks but no defense), θ denotes the weight of failed predictions (i.e., defense but no attack), and FP represents false positive of attack patterns (i.e., defense but no attack).

G-FQL algorithm is compared with existing soft computing methods like Fuzzy Logic Controller (FLC), Q-learning, and Fuzzy Q-learning (FQL), in terms of total energy consumed by sensor nodes and number of alive nodes during the simulation. Results show that the number of alive nodes in G-FQL is greater than the other methods. However, a clear conclusion about the performance of G-FQL in term of energy efficiency is missing. It is also important to note that G-FQL is not fully distributed. Only the detection of an attacker is done by clusters in a distributed manner. However, the algorithm is centralized as all the defense actions are done mainly by the sink.

Discussion and Future Directions

Due to the nature of the problems in this domain, it is unlikely to see proposals that use cooperative games. That is because if nodes could be trusted to cooperate we would not have most of the security problems. However, nodes could cooperate in defending against attackers. Nevertheless, we believe that cooperation enforcement mechanisms are preferable in this domain, in the sense that they guarantee cooperation and make the defending strategy more robust, as in [194]. Evolutionary game theory [189] is also used in defense models [188, 191]. It does not require a global knowledge of the game state, though it allows the nodes to dynamically adjust their defense strategies taking energy consumption costs into account.

Game theory is widely used to address problems derived from nodes that misbehave. Specifically in the cases where they do it for selfish reasons -as opposed to malicious reasons. We foresee that future studies in this domain -for energy efficiency and other issues- will use games that implement reputation schemes, trust models, or attack detection and protection mechanisms such as [192], [190, 191, 193], and [188, 194], respectively.

An innovative design method of combining game theory and computational intelligence for attack detection and protection has been proposed in [194]. [192], [193] and [194] proposes centralized solutions. Hence, it would be interesting to find energy efficient solutions in which the trust model or the protection mechanism are distributed despite the expected challenges that can arise in networks with a large number of nodes.

A recent trend in WSNs is to use data from other WSNs to optimize the operation of a target WSN [195]. For instance, a WSN measuring pollution can use the instantaneous information provided by a WSN measuring the number of cars in a road to adapt its sensing rate to the traffic conditions, thus saving energy when the road is empty. In case the WSNs that exchange data do not belong to the same administrative domain, trustworthiness becomes a fundamental requirement. In this scenario, game theory can help to decide if a WSN may benefit from sharing its data, as well as to guarantee the trustworthiness of the received data.

3.5.3 Task allocation

According to [200], task allocation in WSNs is defined as: (1) the assignment of tasks to sensor nodes, (2) the assignment of communication activities to channels, or (3) the scheduling of computation and communication activities. Recently, task-based systems are needed to provide services to entities outside the network. Allocation of tasks to wireless nodes must take into account energy constraints, as well as the compatibility of tasks to a given node and/or topology.

Non-game theoretic approaches have been applied in this domain like EcoMapS (Energy-constrained Task Mapping and Scheduling) [201]. EcoMapS is an application-independent mechanism. It consists of a scheduling system that aims to map and schedule tasks of an application with minimum schedule length subject to consumption constraints in cluster-based WSNs. Another scheduling problem is how to schedule a given set of tasks on a single node, taking into account energy efficiency, as proposed in [202]. In this proposal, the tasks specify an attribute called ”importance”, also denoted as a power index. It shows the relative importance of a task in relation to other tasks under low-power conditions. An Integer Linear Programming (ILP) formulation and a polynomial time 3-phase heuristic are proposed in [200] in order to formulate the energy-balanced task allocation in a cluster-based WSNs. The goal is to find an allocation that maximizes the lifetime of the cluster. Topology-aware energy efficient task assignment for multi-hop WSNs has been addressed in [203], in which an ant-based meta-heuristic algorithm was developed to optimize the

Table 3.5.1: Proposals in WSN Data Aggregation, Security, and Task Allocation (Section 3.5).

Domain	Article	Algorithm	Year	Game Class	Game Techniques	Method of Energy Savings
Data aggregation	[171]	CAR	2012	Non-cooperative	exact potential game	the cost function takes into account the energy and the correlated data
	[177]	RGTAGN- ACO-R	2012	Non-cooperative	reverse game, repeated game, pure strategy	an energy aware data aggregation by a robust selection of aggregation nodes
Security	[188]	-	2014	Non-cooperative	evolutionary game, incomplete info, mixed strategy	finding the best strategy that balances between the rewards and the costs resulted from deploying the security measures (i.e., energy consumption)
	[190]	TDDG	2014	Non-cooperative	mixed strategy NE	an energy aware trust derivation dilemma game
	[191]	-	2014	Non-cooperative	evolutionary game, mixed strategy NE, best response	an energy aware coordinator selection mechanism
	[192]	TEER	2009	Cooperation Enforcement	NE, incentive mechanism (reputation-based)	electing healthy CHs with the highest energy and trust levels
	[193]	-	2013	Cooperation Enforcement	incentive mechanism (reputation-based), centralized	maintaining a good reputation while saving energy resources
	[194]	G-FQL	2013	Cooperation Enforcement	incentive mechanism (credit-based), centralized	to defend against attackers who send flooding messages that exhaust nodes' energy and prevent nodes from entering the sleeping mode
Task allocation	[196]	NGTSA	2011	Cooperation Enforcement	mechanism design, incentive mechanism (credit-based), private information	splitting the main tasks received by sink into a number of sub-tasks and distributing them to the clusters
	[197]	Centralized WDP	2011	Cooperation Enforcement	reverse auction game, incomplete information	maximizing network lifetime by sharing the tasks and the network resources among applications
	[198]	Distributed ED-WDP	2012	Cooperation Enforcement	reverse auction game, incomplete information	an energy and delay efficient decentralized WDP mechanism
	[199]	-	2012	Cooperation Enforcement	incentive mechanism, mixed strategy, repeated game	serving nodes with the lowest remaining energy level first

task assignment. In [204], simulated annealing [205] method was applied to search an optimal task assignment, aiming to minimize the total energy consumption and latency. The work described in [206] focuses on a scheduling algorithm for the sub-tasks of an application in WSNs. The goal of the task scheduler is to maximize network lifetime. This problem is reduced into a min *k-cut* problem (i.e. a well-studied graph problem), which can be solved in polynomial time.

In the following subsections we present and discuss the latest contributions in this domain that focus on energy efficiency using game theory. The proposals are summarized in Table 3.5.1.

Sensing tasks should be allocated among sensors fairly and in a minimum time. Besides, completing the sensing task in a shorter time will also results in energy savings. However, sensors may refuse to execute a task due to their limited energy resources and act selfishly. To solve this problem, a Non-cooperative Game Task Scheduling Algorithm (NGTSA) is proposed in [196]. The goal is to find an optimal strategy for splitting main tasks received by the sink into a number of sub-tasks, as well as distributing these sub-tasks to clusters in the right order. A utility function related to the total task completion time and tasks allocating scheme is designed. NE is proved. Simulation results illustrate that selfish nodes can be forced to report their true processing capability and participate in the measurement. Thereby, the total time for accomplishing the task is minimized and the energy consumption of nodes is balanced.

In [197], the distributed task allocation problem for multiple concurrent applications in shared WSNs is modeled using a reverse combinatorial auction. In this proposal nodes are models as bidders. Each node bids the cost value in terms of available resources (e.g., energy and CPU) for accomplishing tasks. Each application may consist of several tasks. The main objective is to maximize network lifetime by sharing tasks and network resources among applications, while improving the overall QoS (e.g., deadlines) of each application. Since combinatorial reverse auction problem is a NP-complete problem, a heuristic two-phase Winner Determination Protocol (WDP) is proposed. In the first phase, a local decision maker is developed to eliminate bidders with lower probability of winning. This results in a low overhead for combinatorial auction message exchange. In the second phase, the suboptimal subsets are selected by an ordering heuristic. Simulation experiments are done to evaluate the system efficiency and scalability when the number of concurrent applications and network size increases. Results show a significant difference in terms of energy consumption when the tasks are shared compared to the non-sharing case. Besides, the proposed task allocation scheme outperforms the static energy balanced scheme, Energy Balanced Critical Node Path Three (EB-CNPT) [207], in balancing the energy in the network since the energy level of each sensor is considered in each stage of the proposed task allocation scheme. The architecture of this scheme is illustrated in Fig. 3.5.2.

[198] extends the work presented in [197]. It mentions that given a distributed pool of bids from bidders (i.e., sensor nodes), a centralized Winner Determination Protocol (WDP) may suffer from high energy consumption and overhead related to message exchanges. Hence, [198] proposes an

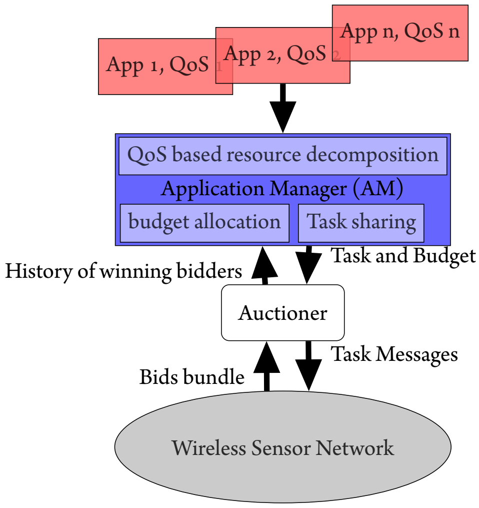


Figure 3.5.2: Market based architecture for multiple task allocation.

Energy and Delay Efficient Distributed Winner Determination Protocol (ED-WDP). Simulation results show that a fairer energy balance can be achieved in comparison to other well-known static schemes. Moreover, in ED-WDP, the message exchange overhead, energy consumption, and delay for winner determination are significantly reduced compared to the centralized WDP.

Few of the previous works notice the constraints on sensors caused by a limited buffer size. Thus, a scheduling policy is proposed in [199]. The scheduler serves firstly nodes with low remaining energy, as well as nodes with the least free buffer storage. This solution prolongs network lifetime and provides a real-time service quality. It also considers the presence of selfish nodes. It shows their negative impact on the system performance in terms of packet loses, network lifetime, and spectrum utilization efficiency. A non-cooperative game model is used. The game converges to an inefficient mixed strategy NE, at which the bandwidth resource is wasted. In order to eliminate user's selfish behavior and enforce cooperation, an incentive mechanism represented by a punishment scheme via a repeated game is added.

Discussion and Future Directions

The proposals used in this field apply cooperation enforcement games. [196] aims to distribute sensing tasks between nodes fairly. It deals with nodes' selfish behavior by forcing them to report their true processing capability. [197, 198] use reverse combinatorial auctions, in which nodes bid the cost value in terms of available resources for accomplishing applications' tasks. Since the combinatorial reverse auction problem is a NP-complete problem, heuristic two-phase winner determination protocols (WDP in [197], ED-WDP in [198]) are proposed to solve it. The difference between WDP and ED-WDP is that the first one is centralized while the other is distributed.

In [199], the selfishness behavior is considered and the enetwork lifetime is prolonged by serving nodes with the least remaining energy and buffer free storage first. This proposal also imposes a punishment scheme to enforce cooperation.

The research in this area is still in its early stages, but it looks very promising. In future work, scenarios that employ nodes of different capabilities should be considered. For example, we can have nodes with multiple sensors that can support several tasks concurrently, or nodes with higher computational capacity that can help others to accomplish their tasks.

3.5.4 Energy Harvesting WSNs

Finally, we overview the work done in game theory related to Energy Harvesting Wireless Sensor Networks (EH-WSNs). Since the number of papers in this area is reduced, we simply describe the papers in this section, including also our thoughts about future research directions in this area.

Energy harvesting technologies comprises a promising solution for WSNs where the battery capacity of sensor nodes is limited and recharging (or replacing) the battery is impractical. In EH-WSNs, an energy harvesting device (e.g., a solar cell) converts different forms of environmental energy into power to supply sensor nodes. In this manner, the nodes could prolong lifetime without a need for battery recharge or replacement. However, since it can produce energy only at a limited rate, energy harvesting introduces fundamental issues in the different domains of WSNs. An overview of the various EH research issues, the energy savings mechanisms, and the EH technologies for WSNs is presented in [104].

Game theory offers tools for solving various problems in EH-WSNs. In general, the energy level of an energy-harvesting sensor varies dramatically according to the time period. Hence, a distributed estimation of the energy level in EH-WSNs is required. In [208], the unpredictable harvested energy, the battery level, and energy consumption are modeled together in a unified way using game theory. The formulated game has complete and perfect information. A sub-game perfect NE is derived by backward induction. Simulation results show that the proposed model improves the use of the harvested energy and enhances the estimation of the energy level of the nodes.

Another crucial problem in this area that is suitable to be addressed using game theory is optimizing the remaining energy of an energy-harvesting sensor. The goal is to satisfy the required

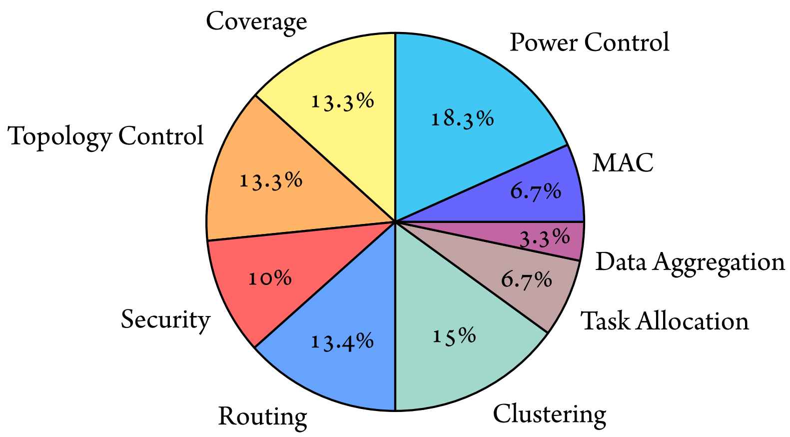


Figure 3.5.3: The percentage of latest proposals in each domain of WSNs.

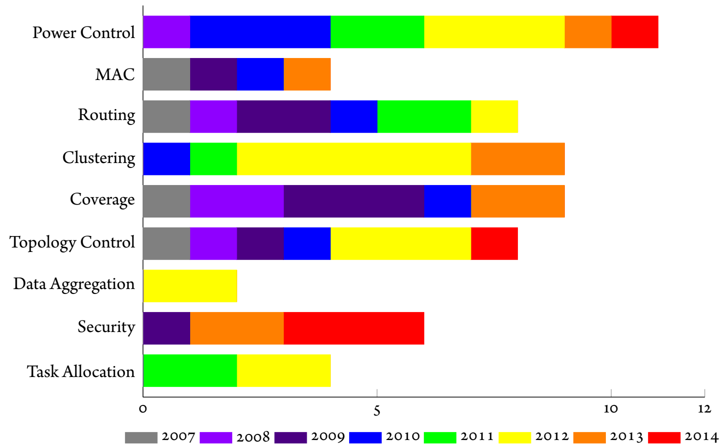


Figure 3.5.4: The distribution of WSN problems over years.

QoS at a regular basis under varying amounts of power caused by the ambient or climatic changes (e.g., cloudy or stormy weather).

Finally, the different domains of WSNs (i.e., power control mechanisms, MAC, and routing protocols, among others) need to be extended and adapted to cope with the properties and challenges imposed by EH sensors.

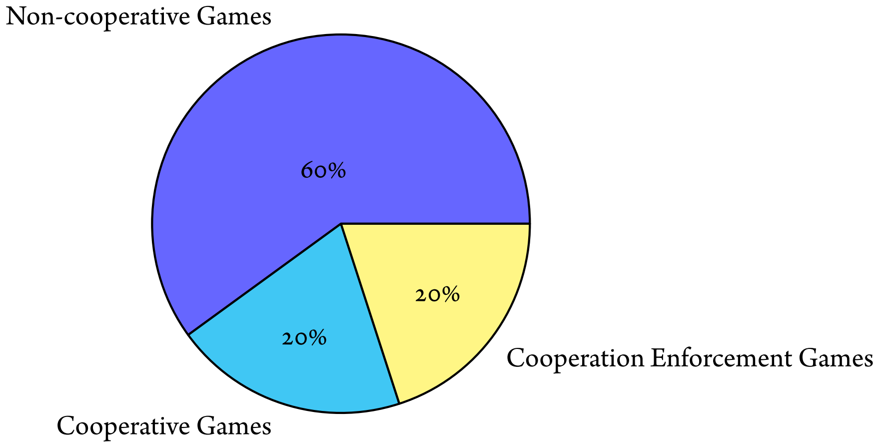


Figure 3.5.5: The percentage of reviewed game theory proposals of the three main classes.

3.6 Conclusions

In this chapter we present and discuss the state-of-the-art of game theory approaches for addressing energy efficiency and lifetime maximization problems in different domains of WSNs including power control, MAC, and routing, among others. We classify the space of games into three main classes: i) non-cooperative, ii) cooperative, and iii) cooperation enforcement games. Recent proposals in the different WSNs domains that employ different classes of games are surveyed, and the various game theory concepts used are presented. Then, methods used by each proposal for achieving energy efficiency and/or lifetime maximization are explained.

Each domain starts with an introduction which presents and discusses the recent work done for addressing the energy efficiency problem in that domain using non-game theory approaches. Then, we present the different game theory proposals. At the end of each domain, we specify a separate section for discussion and future directions. It places special emphasis on i) lessons learned in each domain, ii) what is the most appropriate game class for that domain, iii) strength and pitfalls of proposals, and iv) a guidance about some gaps that need to be addressed in future work.

In addition, comparative tables and statistical charts (see Fig. 3.5.3, 3.5.4 and 3.5.5) are presented to overview how this research area has evolved in the last few years. Fig. 3.5.3 and 3.5.4 are specially interesting, since they illustrate the amount of work in each domain over the years. We can notice that the area that attracts most researchers is routing and clustering, followed by power control. This is because of the diversity and importance of issues that need to be solved in those areas. Finally, it is noticeable that the game theory models used for addressing energy efficiency vary from one domain to another, as they depend on the specific problem being solved.

4

Energy Efficiency of MAC Protocols in Low Data Rate Wireless Multimedia Sensor Networks

4.1 Introduction

In this chapter we study the energy efficiency of the MAC layer in non-streaming delay-tolerant WMSNs by modeling and evaluating the energy consumption of several and different MAC protocols, designed for traditional WSNs, taking into account the existence of MMSs in the network. The study addresses the spectrum of low data rate applications where the main target is to minimize the energy consumption and increase the lifetime of the sensor network, as discussed in Chapter 2. Therefore, the selected MAC protocols should be those ones which improve the energy efficiency, regardless if they are QoS-aware or if they provide constant bandwidth -as required by streaming applications.

To achieve this goal we develop a multi-class traffic model that allows to integrate different types of sensors with different sampling rates. This traffic model is an extension and a generalization of the one presented in [30], where the network topology is abstracted by detailing for every node what input traffic it is handling, and what overhearing traffic is bothering it being sent out by its neighbors. The extended model allows to integrate input traffic from both MMSs and SSs which sample the environment at different rates. This helps in analyzing the effects of various parameters of MMSs -such as the sampling rate, the density and the size of multimedia sample- on the traffic each node transmits, receives and overhears.

There are previous works on modeling and evaluating the energy consumption of MAC protocols in WSNs like [30, 209]. However, none of those studies models and evaluates the energy consumption of MAC protocols in WMSNs. Moreover, there is a lack of comparisons between the energy consumption of recent MAC protocols and the early designed ones. Therefore, the main goal of this study is to assess and compare the energy performance of those MAC protocols in low data rate WMSNs, under variable sampling rates and densities of MMSs, in order to find out the suitable MAC protocols for this kind of networks and its application scenarios.

The rest of the chapter is organized as follows: In Section 4.2, the design principles are presented and the multi-class traffic model is derived. The energy consumption of MAC protocols is modeled in Section 4.3 and Section 4.4. In Section 4.5, we conduct a numerical evaluation of the energy performance of MAC protocols under different configurations of WMSNs and in various application scenarios. Finally, the chapter is concluded in Section 4.6.

The work presented in this chapter has been accepted for publication in [210].

4.2 System Model and Assumptions

4.2.1 Design Principles

We focus on a WMSN that consists of a sink, SSs and MMSs with a continuous monitoring mode in which nodes take a sample at periodic intervals. Nodes are static and strategically placed in D rings in an increasing number (i.e., rings close to the sink have less nodes than outer rings). The farthest nodes are located in ring d=D and the sink is labeled as d=0. Each node has a set of input nodes I and a set of overheard nodes H. This allows for accurate modeling of both regular topologies like ring and grid topologies, as well as irregular deployment scenarios. An illustrative example of the considered ring topology is depicted in Fig. 4.2.1.

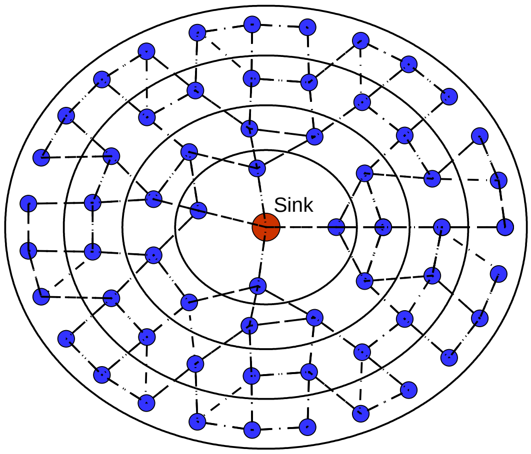
The communication pattern is a data gathering tree with traffic flowing hop-by-hop from the leaves (i.e., nodes at different levels) to the root (i.e., the sink) which is placed in the center of the area. Each node is in the communication range with C neighbors. Routes to the sink are selected according to the Shortest Path First (SPF) algorithm [211] and they are fairly durable, so that a data gathering tree remains stable during the observation time. All sensors use the same radio data rate R. Any sensor in the network generates its own traffic (i.e., after taking a sample from the environment) and relays incoming traffic from upper rings. We assume perfect links where external interference is negligible [30]. This assumption will allow us to exclusively focus on the characteristics of the MAC protocols, providing a better understanding of the pure energy consumption behavior of each one without external factors. We also assume that the sampling rates of sensors within the WMSN are low enough to consider the collision probability negligible [27, 30], including those with hidden nodes. However, we will include later in the study some load constraints to limit the amount of traffic flowing through the network in order to make collisions negligible.

4.2.2 Traffic Model

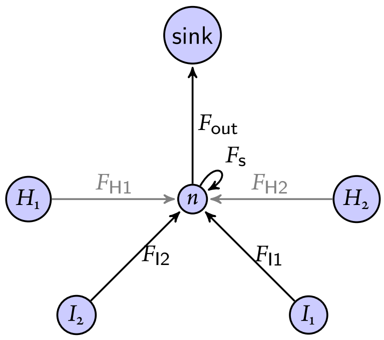
For deriving the traffic model, we extend the one proposed by Langendoen [30], which models the traffic flowing through nodes to the sink in a homogeneous sampling rate sensor network, to a model for a multi-class sampling rate sensor network in which we have L classes of nodes, where each class has its own sampling rate. For each node, let F_s be the rate at which it samples the environment, F_I the rate of incoming traffic it has to forward, and F_H the rate of traffic it overhears, which is caused by neighboring nodes. Fig. 4.2.1(b) gives an example of the traffic model for a given node n. The overhearing traffic is generated by nodes H_1 and H_2. F_{I_1} and F_{I_2} are the rates of incoming traffic. F_{out} is the total output traffic rate, which includes the rate of self-generated traffic F_s, and the total incoming traffic it has to forward F_I.

In a similar way as in [30], N nodes are deployed in the area with a uniform node density. Assuming a unit disk graph communication model, each unit disk contains C+1 nodes on average. Thus, all nodes are in communication range with a fixed number of neighbors C. As mentioned before, the nodes are located in D rings according to their distance to the sink (i.e, in d=0). The first ring contains C nodes, from which we can derive the average number of nodes N_d in ring d as follows:

$$N_d = \begin{cases} 1 & d{=}0 \\ Cd^2 - C(d-1)^2 = (2d-1)C & \text{otherwise.} \end{cases} \tag{4.1}$$



(a) The actual network topology (D=4, C=4).



(b) Overview of the traffic model.

Figure 4.2.1: Network Topology and Traffic Model.

Let us assume a general case where there are L classes of sensors, and the nodes sample the environment at a rate F_s^l, according to the class they belong to, where $l \in 1, \ldots, L$. At each ring there is a percentage p_l of nodes of class l, and the average number of nodes in ring d for each class is $N_\mathrm{d}^l = p_l(2d-1)C$, while the average number of input links of class l is given by the formula:

$$\begin{aligned} I_\mathrm{d}^l &= \frac{N_\mathrm{d+1}^l}{N_\mathrm{d}} \\ &= p_l \frac{(2d+1)}{(2d-1)}. \end{aligned} \tag{4.2}$$

We take a node of class l at a ring d that has an incoming traffic of class i, and define $F_{\mathrm{out}}^{d,l,i}$ as the output traffic of class i for this node as follows:

$$F_{\mathrm{out}}^{d,l,i} = \begin{cases} 0 & d = 0, \forall i \\ F_\mathrm{I}^{d,i} & 0 < d < D, i \neq l \\ F_s^l + F_\mathrm{I}^{d,l} & 0 < d < D, i = l \\ F_s^l & d = D, i = l \\ 0 & d = D, i \neq l, \end{cases} \tag{4.3}$$

where $F_\mathrm{I}^{d,i}$ is the incoming traffic rate of class $i \in 1, \ldots, L$ in ring d. The incoming traffic is on average the same for any node at the same ring, since these nodes have an equal average number of input links of any class, and it is given by the following formula:

$$F_\mathrm{I}^{d,i} = \frac{(D^2 - d^2)}{(2d-1)} p_i F_s^i. \tag{4.4}$$

Using formula (2) we can distinguish between the average incoming traffic coming from each class of sensors.

The overhearing traffic for a node in ring d from class i is given by the following formula:

$$F_\mathrm{H}^{d,i} = \sum_{l=1}^{L} (N_\mathrm{d}^l - I_\mathrm{d}^l) F_{\mathrm{out}}^{d,l,i}. \tag{4.5}$$

We differentiate between the class of a given node and the class of traffic it forwards using the

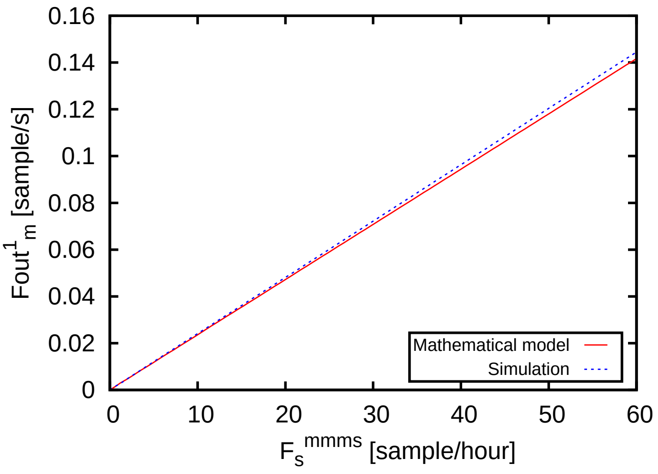


Figure 4.2.2: Validation of the mathematical model.

notations l and i, respectively. The proposed traffic model allows the usage of different sampling rates depending on the class of sensors. To validate this model we simulate a uniformly distributed topology in which we threw 64 sensors randomly around a sink and took a node near the sink (i.e., 1-hop distance) to calculate its average output traffic rate of around 50 runs. The paths are selected according to the SPF algorithm. The sensors are grouped based on their distance to the sink. The average output traffic rate in the random topology and the mathematical model are calculated and compared in Fig. 4.2.2. It can be observed that the mathematical model is within 2-4% of the value determined by the random topology.

4.2.3 Multimedia Sampling Rate

Assume we have two types of sensors: SSs and MMSs. MMSs are equipped with cameras and devoted to object detection and object monitoring duties. To do that, MMSs periodically take an image at a rate F_s^{mms} and send the image to the sink. The sampling rate, defined as the frequency at which an image is taken, can range from tens of seconds to hours. Every time an image is taken, depending on the image size (e.g., in pixels), and the coding and compression scheme, a MMS will generate data that is larger than a single layer 2 payload. Thus, every multimedia sample is divided and represented by M payloads, being the size of M dependent on the image taken, and the coding and compressing mechanisms. The size of each multimedia payload depends on the multimedia content and can reach a max value P^m.

As an example, for a 64x64 pixel image, with Red-Green-Blue (RGB) coding (i.e., 24-bit per pixel), an image will have a size of around 100KB. Assuming compression ratios of 90% or less (e.g., after a background subtraction process), the image size can be reduced to near 10KB or less, hence, with a layer 2 payload (P^m), of a size 512B for instance, a MMS will generate around M=20 payloads each of a size P^m=512B. Thus, when accounting for the energy spent in sending and receiving every multimedia sampling, M payloads have to be taken into account. Later in the study we will show how the size of the multimedia sample (i.e., the value of M) affects the maximum allowed sampling rate of MMSs (F_s^{mms}).

In the case of SS nodes, the sampling rate is also quite low (e.g., one sample per minute) and every sample produces a single packet. The data retrieved by SS nodes is relatively small and could be fit in one single payload P^s. It is clear that the self-generated traffic by MMSs (F_s^{mms}) will be much higher than by SSs (F_s^{ss}), however, we stress that the MMSs' sampling rate (e.g., the number of images taken per second) is low enough to do not cause congestion or queuing delays.

4.2.4 Sampling Energy Consumption

Since the multimedia applications we are considering are environment monitoring or object detection, we use low cost, low power and low resolution camera sensors like Cyclops [48]. We assume that the amount of power consumed in the subsystems of a MMS is considerably higher than of a SS. For example a temperature SS consumes $P_{\mathrm{ss}} = 6\ \mu\mathrm{W}$ for sensing the environment [212], while a MMS that uses a tiny Cyclops camera consumes $P_{\mathrm{mms}} = 42$ mW for capturing an image [213]. We also assume that MMSs do in-node processing and compression of the multimedia content before sending the image to downstream nodes in order to reduce traffic by reducing the size of images and the number of payloads. Let us call e_{s}^{l} the energy spent in capturing and processing a sample from the environment for a node of class l (e.g., $e_{\mathrm{s}}^{\mathrm{mms}}$ if it is a MMS), then the energy spent in sampling the environment is:

$$E_{\mathrm{s}}^{l} = F_{\mathrm{s}}^{l} e_{\mathrm{s}}^{l}. \tag{4.6}$$

Table 4.2.1: Parameters of the radio used (CC2420) and the traffic model with the corresponding values (used in Sections 4.3, 4.4 and 4.5).

Parameter	Description	Value
R	Data rate (kbyte/s)	31.25
T_{cs}	Time for carrier sense (ms)	2.5
θ	Frequency tolerance (ppm)	30
T_{SIFS}	Short inter-frame space (μs)	11
L_{ack}	Acknowledgment length (byte)	12
L_{hdr}	Message header length (byte)	12
P^m	Size of a multimedia payload (byte)	512
P^s	Size of a scalar payload (byte)	32
MM	Image size (kbyte)	10
M^m	Number of multimedia Payloads	20
M^s	Number of scalar Payloads	1
F_s^{ss}	Sampling frequency of scalar sensors (samples/hour)	[0, 120]
F_s^{mms}	Sampling frequency of multimedia sensors (samples/hour)	[0, 60]
p_{m}	Percentage of multimedia sensors (%)	[0, 100]

4.3 Energy Models for Asynchronous MAC Protocols in WMSNs

In this section we model the energy consumption of some baseline and recent asynchronous duty-cycling MAC protocols including both sender-initiated transmission like B-MAC [32] and X-MAC [33], and receiver-initiated transmission like RI-MAC [34] and PW-MAC [35].

4.3.1 Sender-Initiated MAC Protocols:

B-MAC

Berkeley MAC [32] is an asynchronous MAC protocol for WSNs, in which each node periodically performs a carrier sense to detect the radio channel state during a short period, which is known as *Low Power Listening (LPL)*. If the channel is clear, a sender can hold the channel and send the data, which is preceded by a preamble, to ensure a correct reception by all potential receivers who are duty cycling. Potential receivers stay awake to receive the data when an activity in the channel is detected (i.e, the preamble), see Fig. 4.3.1. This reduces the idle-listening overhead without the need for an explicit synchronization between nodes, but it comes at the expense of sending out a long preamble that covers one complete polling interval T_{w}. The parameters of B-MAC are given

Table 4.3.1: Parameters of the considered sender-initiated asynchronous MAC protocols and their values (used in Sections 4.3 and 4.5).

	Parameter	Description	Value
B-MAC	T_w	Polling period (s)	[0.02, 0.5]
X-MAC	T_w	Polling period (s)	[0.02, 0.5]
	L_{sp}	Short Preamble length (byte)	12
	T_{ea}	A gap between short preambles for early ACK (ms)	3.75

Table 4.3.2: The power consumed in each mode and its corresponding values. These values are used in Sections 4.3, 4.4 and 4.5.

Parameter	Description	Value
P_{tx}	Power in transmission mode (mW)	[52.2]
P_{rx}	Power in receiving mode (mW)	[56.4]
P_{idl}	Power in idle listening mode (mW)	[56.4]
P_{mms}	Power for capturing an image (mW)	[42]

in Table 4.2.1 and 4.3.1. The sources of energy consumption in B-MAC are the energy spent in performing a regular carrier sense e_{cs}, transmitting e_{tx}, receiving e_{rx}, overhearing e_{ov} and the energy spent in taking a sample from the environment e_s. The power drawn in each mode are P_{idl}, P_{tx}, P_{rx} and P_s, respectively and their values are given in Table 4.3.2.

The time required to transmit, receive and overhear a packet of class i in B-MAC is:

$$\begin{aligned} T^i_{tx} &= T_{cs} + T_w + T^i_{msg}, \\ T^i_{rx} &= \frac{T_w}{2} + T^i_{msg}, \\ T_{ov} &= \frac{T_w}{2} + T_{hdr}, \end{aligned} \tag{4.7}$$

respectively, where T_{cs} is the time spent in sensing the channel, T_w is the polling period of a receiver and it represents the length of the preamble, and T^i_{msg} is the time required for sending one payload of class i. Each payload is preceded by a packet header and followed by an acknowledgement. We account also for the radio switch delay by adding T_{SIFS} as follows:

$$T^i_{msg} = T_{hdr} + \frac{P^i}{R} + T_{SIFS} + T_{ack}. \tag{4.8}$$

The energy spent in each mode is:

$$
\begin{aligned}
e^{i}_{\mathrm{tx}} &= \left(T_{\mathrm{cs}} + T_{\mathrm{SIFS}}\right) P_{\mathrm{idl}} + \left(T_{\mathrm{w}} + T_{\mathrm{hdr}} + \frac{P^{i}}{R}\right) P_{\mathrm{tx}} \\
&\quad + T_{\mathrm{ack}} P_{\mathrm{rx}}, \qquad (4.9)\\
e^{i}_{\mathrm{rx}} &= T_{\mathrm{SIFS}} P_{\mathrm{idl}} + \left(\frac{T_{\mathrm{w}}}{2} + T_{\mathrm{hdr}} + \frac{P^{i}}{R}\right) P_{\mathrm{rx}} + T_{\mathrm{ack}} P_{\mathrm{tx}}, \qquad (4.10)\\
e_{\mathrm{ov}} &= \left(\frac{T_{\mathrm{w}}}{2} + T_{\mathrm{hdr}}\right) P_{\mathrm{rx}}, \qquad (4.11)\\
e_{\mathrm{cs}} &= T_{\mathrm{cs}} P_{\mathrm{idl}}. \qquad (4.12)
\end{aligned}
$$

We calculate the energy consumption in each mode during a given observation time T_{obs}. The time in which a node of class l is active in T_{obs} represents the total transmitting, receiving and overhearing times, and is given by the following:

$$
\begin{aligned}
T^{d,l}_{\mathrm{active}} = T_{\mathrm{obs}} \Bigg(&\left(M^{l} F^{l}_{\mathrm{s}} T^{l}_{\mathrm{tx}} + \sum_{i=1}^{L} M^{i} F^{d,i}_{\mathrm{I}} T^{i}_{\mathrm{tx}} \right) + \left(\sum_{i=1}^{L} M^{i} F^{d,i}_{\mathrm{I}} T^{i}_{\mathrm{rx}} \right) \\
&+ \left(\sum_{i=1}^{L} M^{i} F^{d,i}_{\mathrm{H}} T_{\mathrm{ov}} \right) \Bigg), \qquad (4.13)
\end{aligned}
$$

and the inactive time is calculated as follows:

$$
T^{d,l}_{\mathrm{inactive}} = T_{\mathrm{obs}} - T^{d,l}_{\mathrm{active}}, \qquad (4.14)
$$

where M^{l} is the number of payloads of class l, F^{l}_{s} is the rate at which a node of class l samples the environment, $F^{d,i}_{\mathrm{I}}$ is the incoming traffic rate of any class i in ring d, and $F^{d,i}_{\mathrm{H}}$ is the overhearing traffic from any class i in ring d.

Then, the total energy consumed in T_{obs} in each state is:

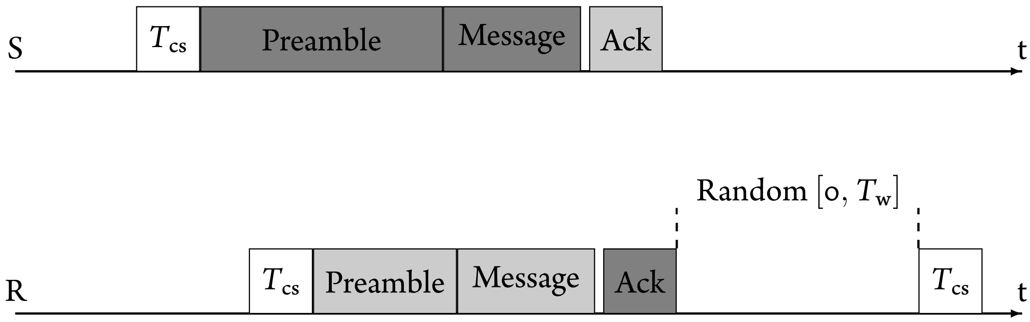


Figure 4.3.1: B-MAC.

$$E_s^l = \left(F_s^l e_s^l\right) T_{obs}, \tag{4.15}$$

$$E_{tx}^{d,l} = \left(M^l F_s^l e_{tx}^l + \sum_{i=1}^{L} M^i F_I^{d,i} e_{tx}^i\right) T_{obs}, \tag{4.16}$$

$$E_{rx}^{d,l} = \left(\sum_{i=1}^{L} M^i F_I^{d,i} e_{rx}^i\right) T_{obs}, \tag{4.17}$$

$$E_{ov}^{d,l} = \left(\sum_{i=1}^{L} M^i F_H^{d,i} e_{ov}\right) T_{obs}, \tag{4.18}$$

$$E_{cs} = T_{inactive} \frac{T_{cs}}{T_w} e_{cs}, \tag{4.19}$$

$$E_{ctrl}^{d,l} = 0. \tag{4.20}$$

Except where otherwise stated, in the modeling of the next MAC protocols, these equations are computed the same way and they will not be displayed.

Then we compute the total energy consumption as follows:

$$E_{T_{obs}}^{d,l} = E_s^l + E_{tx}^{d,l} + E_{rx}^{d,l} + E_{ov}^{d,l} + E_{cs} + E_{ctrl}^{d,l}, \tag{4.21}$$

where $E_{ctrl}^{d,l}$ refers to that energy consumed by sending and receiving control packets (e.g., synchronization messages) which is zero in the case of B-MAC.

X-MAC

X-MAC [33] divides the long preamble in B-MAC into a series of short preamble bursts of duration T_{sp}. Because the destination address is included in the short preambles, non-target receivers can immediately go back to sleep after receiving a short preamble packet, which reduces the energy spent in overhearing. The short preamble bursts are interleaved with short idle times of duration T_{ea} to allow a receiver to reply with an *early acknowledgment*. Whenever a sender receives an early ACK from the intended receiver, it stops sending the preamble bursts and starts sending the data packets.

Introducing the early acknowledgement could achieve considerable energy savings by reducing the preamble length to half on average compared to B-MAC, but comes at the price of an increased time for carrier sensing (i.e., $T_{\text{cs}} + T_{\text{ea}}$) each time a node wakes up. A node turns off its radio if the medium has been idle for a time longer than the gap duration between two short preambles. X-MAC mechanism is illustrated in Fig. 4.3.2 and its parameters are given in Table 4.2.1 and 4.3.1.

The time required to transmit, receive and overhear a packet of class i in X-MAC is:

$$\begin{aligned} T^{i}_{\text{tx}} &= T_{\text{cs}} + T_{\text{ea}} + \frac{T_{\text{w}}}{2} + T_{\text{SIFS}} + T^{i}_{\text{msg}}, \\ T^{i}_{\text{rx}} &= 1.5(T_{\text{sp}} + T_{\text{ea}}) + T_{\text{SIFS}} + T^{i}_{\text{msg}}, \\ T_{\text{ov}} &= 1.5(T_{\text{sp}} + T_{\text{ea}}), \end{aligned} \tag{4.22}$$

respectively, where:

$$T_{\text{w}} = N_{\text{sp}}(T_{\text{cs}} + T_{\text{ea}}), \tag{4.23}$$

where N_{sp} is the number of short preambles.

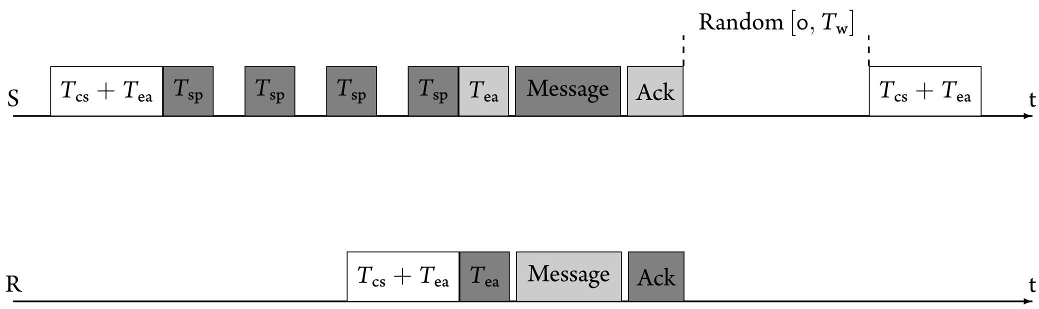


Figure 4.3.2: X-MAC.

The energy spent in each mode is:

$$e^i_{tx} = (T_{cs} + T_{ea} + 2T_{SIFS})P_{idl} + \left(\frac{T_w}{2} + T_{hdr} + \frac{P^i}{R}\right) P_{tx} + T_{ack}P_{rx}, \tag{4.24}$$

$$e^i_{rx} = 2T_{SIFS}P_{idl} + \left(1.5(T_{sp} + T_{ea}) + T_{hdr} + \frac{P^i}{R}\right) P_{rx} + T_{ack}P_{tx}, \tag{4.25}$$

$$e_{ov} = 1.5(T_{sp} + T_{ea})P_{rx}, \tag{4.26}$$

$$e_{cs} = (T_{cs} + T_{ea})P_{idl}, \tag{4.27}$$

$$e_{ctrl} = 0. \tag{4.28}$$

Similar to B-MAC, the total energy consumption in X-MAC is:

$$E^{d,l}_{T_{obs}} = E^l_s + E^{d,l}_{tx} + E^{d,l}_{rx} + E^{d,l}_{ov} + E_{cs}. \tag{4.29}$$

4.3.2 Receiver-Initiated MAC Protocols:

RI-MAC

To improve energy efficiency, receiver-initiated probing has been adopted in some asynchronous MAC protocols. In this type of MAC protocols, a sending node does not start transmitting until the receiver is ready to receive. Receiver-Initiated MAC (RI-MAC) [34] aims at minimizing the

Table 4.3.3: Parameters of the considered reciever-initiated asynchronous MAC protocols and their values (used in Sections 4.3 and 4.5).

	Parameter	Description	Value
RI-MAC	T_w	Polling period (s)	[0.02, 0.5]
	L_b	Beacon length (byte)	12
PW-MAC	T_w	Polling period (s)	[0.02, 0.5]
	T_{ss}	A sender S waits a short period before a receiver R wakes up (ms)	5
	L_b	Beacon length (byte)	12
	L_{ps}	Prediction State: seed of R + time diff between S and R + last wakeup of R (byte)	2+4+4=10

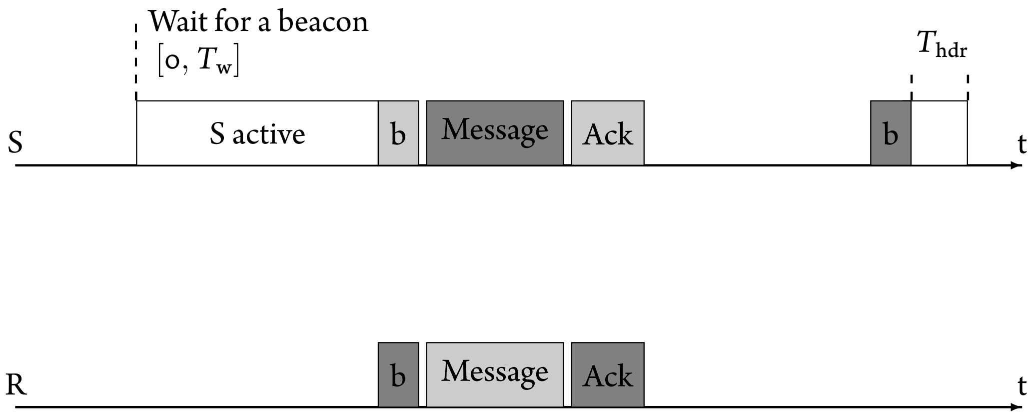


Figure 4.3.3: RI-MAC.

time during which a sender and its intended receiver are occupying the wireless medium to find a rendezvous. Each node wakes up periodically and sends a short beacon to notify potential transmitters that it is awake and ready to receive data. When a node wants to transmit, it samples the channel and remains active (i.e., for an average period $T_w/2$) until receiving a beacon of duration T_b from its intended receiver. After receiving the beacon, the transmitter starts sending the data message, as shown in Fig. 4.3.3. The parameters of RI-MAC are given in Table 4.2.1 and 4.3.3.

The time required to transmit, receive and overhear a packet of class i in RI-MAC is:

$$\begin{aligned}
T^i_{\mathrm{tx}} &= \frac{T_{\mathrm{w}}}{2} + T_b + T_{\mathrm{SIFS}} + T^i_{\mathrm{msg}}, \\
T^i_{\mathrm{rx}} &= T_{\mathrm{b}} + T_{\mathrm{SIFS}} + T^i_{\mathrm{msg}}, \\
T_{\mathrm{ov}} &= T_{\mathrm{b}} + T_{\mathrm{SIFS}} + T_{\mathrm{hdr}},
\end{aligned} \tag{4.30}$$

respectively. Then, after transmitting a beacon, a node expects the incoming packet within a small window T_{hdr}, as shown in Fig. 4.3.3. If the node is not the intended receiver it overhears the header only.

The energy spent in each mode is:

$$\begin{aligned}
e^i_{\mathrm{tx}} = & \left(\frac{T_{\mathrm{w}}}{2} + 2T_{\mathrm{SIFS}}\right) P_{\mathrm{idl}} + \left(T_{\mathrm{hdr}} + \frac{P^i}{R}\right) P_{\mathrm{tx}} \\
& + (T_{\mathrm{b}} + T_{\mathrm{ack}})P_{\mathrm{rx}},
\end{aligned} \tag{4.31}$$

$$e^i_{\mathrm{rx}} = 2T_{\mathrm{SIFS}}P_{\mathrm{idl}} + \left(T_{\mathrm{hdr}} + \frac{P^i}{R}\right) P_{\mathrm{rx}} + (T_{\mathrm{b}} + T_{\mathrm{ack}})P_{\mathrm{tx}}, \tag{4.32}$$

$$e_{\mathrm{ov}} = T_{\mathrm{b}}P_{\mathrm{tx}} + T_{\mathrm{SIFS}}P_{\mathrm{idl}} + T_{\mathrm{hdr}}P_{\mathrm{rx}}, \tag{4.33}$$

$$e_{\mathrm{b}} = T_{\mathrm{b}}P_{\mathrm{tx}}, \tag{4.34}$$

$$e_{\mathrm{ctrl}} = 0. \tag{4.35}$$

The total energy consumption in T_{obs} is:

$$E^{d,l}_{T_{\mathrm{obs}}} = E^l_{\mathrm{s}} + E^{d,l}_{\mathrm{tx}} + E^{d,l}_{\mathrm{rx}} + E^{d,l}_{\mathrm{ov}} + E_{\mathrm{b}}, \tag{4.36}$$

where the total energy spent in sending out a periodic beacon message in receiver-initiated MAC protocols is calculated in a similar way as the total energy spent in carrier sensing in sender-initiated MAC protocols (see Eq. 4.19) and it is given by the following formula:

$$E_{\mathrm{b}} = T_{\mathrm{inactive}} \frac{T_{\mathrm{b}}}{T_{\mathrm{w}}} e_{\mathrm{b}}. \tag{4.37}$$

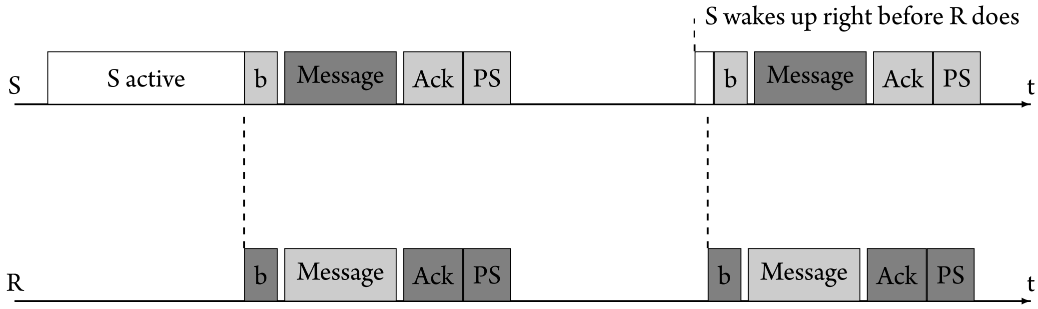


Figure 4.3.4: PW-MAC.

PW-MAC

Predictive wake-up MAC (PW-MAC) [35] is an asynchronous receiver-initiated MAC protocol which reduces the duty cycle at both the receiver and the sender. The goal of PW-MAC is for a sender S to wake up right before its intended receiver R does. As in RI-MAC, each node periodically wakes up and broadcasts a beacon of duration T_{b} to announce that it is awake and ready to receive data packets. If S has a packet to send to R, S turns on its radio and waits for a beacon from R. Upon receiving R's beacon, S transmits its data packets, setting a special flag in the data packet header to request R's *prediction state*. Then, R sends an ACK followed by a short packet of duration T_{ps} in which it embeds its current time and prediction state (PS). The current time of R is used by S to compute the time difference between S and R's clocks. Thus, using the prediction information, node S can predict future wake-up times of R. The PS of R represents the expected time at which R will wake up next time. In the future, when S has data packets to R, S wakes up for only a short duration T_{ss} right before the predicted wake-up time of R. In contrast to RI-MAC, in which a sender stays awake for on average a half wake-up interval waiting for R, PW-MAC significantly reduces this idle listening time once the prediction state of the receiver is learned by the sender. The mechanism of PW-MAC is illustrated in Fig. 4.3.4 and its parameters are given in Table 4.2.1 and 4.3.3.

The time required to transmit, receive and overhear a packet of class i in PW-MAC is:

$$\begin{aligned} T^i_{\mathrm{tx}} &= T_{\mathrm{ss}} + T_{\mathrm{b}} + T_{\mathrm{SIFS}} + T^i_{\mathrm{msg}} + T_{\mathrm{ps}}, \\ T^i_{\mathrm{rx}} &= T_{\mathrm{b}} + T_{\mathrm{SIFS}} + T^i_{\mathrm{msg}} + T_{\mathrm{ps}}, \\ T_{\mathrm{ov}} &= T_{\mathrm{b}} + T_{\mathrm{SIFS}} + T_{\mathrm{hdr}}, \end{aligned} \tag{4.38}$$

respectively, and the energy spent in each mode is:

$$e_{\mathrm{tx}}^{i} = 2T_{\mathrm{SIFS}}P_{\mathrm{idl}} + \left(T_{\mathrm{hdr}} + \frac{P^{i}}{R}\right)P_{\mathrm{tx}} + (T_{\mathrm{b}} + T_{\mathrm{ack}} + T_{\mathrm{ps}})P_{\mathrm{rx}}, \tag{4.39}$$

$$e_{\mathrm{rx}}^{i} = 2T_{\mathrm{SIFS}}P_{\mathrm{idl}} + \left(T_{\mathrm{hdr}} + \frac{P^{i}}{R}\right)P_{\mathrm{rx}} + (T_{\mathrm{b}} + T_{\mathrm{ack}} + T_{\mathrm{ps}})P_{\mathrm{tx}}, \tag{4.40}$$

$$e_{\mathrm{ov}} = T_{\mathrm{SIFS}}P_{\mathrm{idl}} + T_{\mathrm{hdr}}P_{\mathrm{rx}} + T_{\mathrm{b}}P_{\mathrm{tx}}, \tag{4.41}$$

$$e_{\mathrm{b}} = T_{\mathrm{b}}P_{\mathrm{tx}}, \tag{4.42}$$

$$e_{\mathrm{ctrl}} = 0. \tag{4.43}$$

Similar to RI-MAC, there is no explicit channel sensing in PW-MAC. A nodes sends out periodically a beacon message. Moreover, the times spent in sending and receiving the control packet (T_{ps}) are included in the transmission and reception times in Eq. 4.38.

The total energy consumption in PW-MAC in T_{obs} is:

$$E_{T_{\mathrm{obs}}}^{d,l} = E_{\mathrm{s}}^{l} + E_{\mathrm{tx}}^{d,l} + E_{\mathrm{rx}}^{d,l} + E_{\mathrm{ov}}^{d,l} + E_{\mathrm{b}}. \tag{4.44}$$

4.4 Energy Models for Synchronous MAC Protocols in WMSNs

4.4.1 Locally Synchronized MAC Protocols

Locally synchronized MAC protocols allow nodes to turn on their radio at synchronized times and turn them off when no communication occurs during some time. A node determines its next wake-up time and broadcasts its schedule before going back to sleep. Although the communication in locally synchronized MAC protocols is grouped at the beginning of each schedule, raising the chances of collisions, they do not face the problem of finding a rendezvous between nodes as in asynchronous MAC protocols.

T-MAC

S-MAC [36] uses a fixed duty cycle which results in an energy waste in idle listening when traffic load fluctuates. It runs at a duty cycle that matches the load of the busiest node in the network. For this reason, S-MAC is not recommended when the traffic load does not remain constant and predictable. Timeout-MAC (T-MAC) [37] is an extension of S-MAC that allows a dynamic adap-

Table 4.4.1: Parameters of the considered locally-synchronized MAC protocol and their values (used in Sections 4.4 and 4.5).

	Parameter	Description	Value
T-MAC	L_{RTS}, L_{CTS}	Request-to-Send, Clear-to-Send (byte)	12
	CW	Contention Window	1024
	T_{sync}	Time between synchronization messages (s) ($F_{sync} = 1/T_{sync}$)	60
	T_{slot}	Duration of an active period (s)	[0.1, 1]

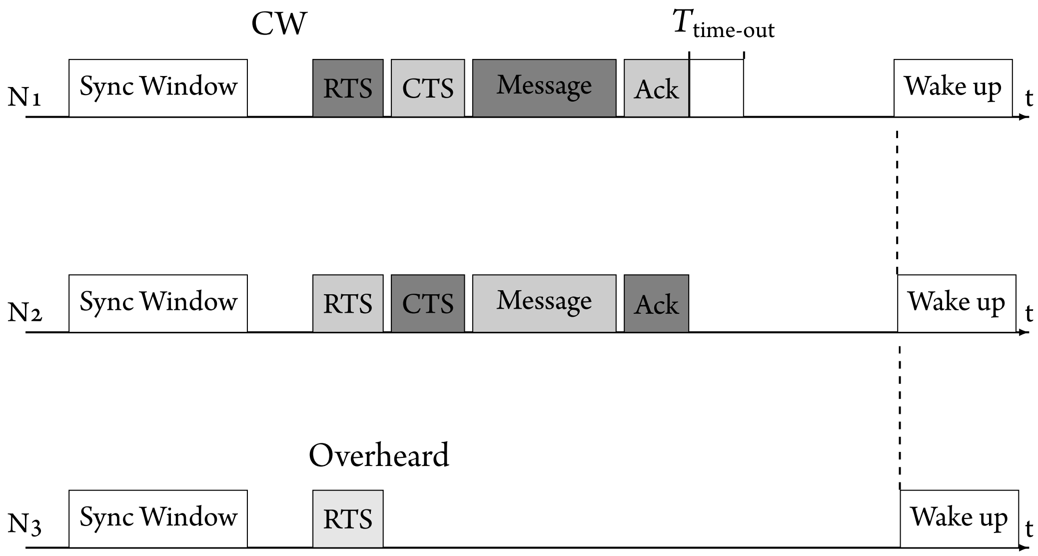


Figure 4.4.1: T-MAC.

tation of the duration of the active period (T_{slot}) to the actual load. The active period is dynamically extended or ended according to a certain time-out period $T_{\text{time-out}}$. Time-outs present a simple but effective way to address the idle listening problem when network traffic load varies. T-MAC mechanism is illustrated in Fig. 4.4.1 and its parameters are given in Table 4.2.1 and 4.4.1.

Nodes in T-MAC wake up periodically. During the active periods, they contend for the channel -if they have packets to send- in a contention window of duration T_{CW}, then they exchange Request-to-Send (RTS) and Clear-to-Send (CTS) packets followed by the actual payload.

Nodes also exchange synchronization messages periodically. At the beginning of each synchronization period, a node sends one synchronization header, and receives synchronization headers from its one-hop neighbors (i.e., each node has C neighbors as mentioned in Section 4.2) at a rate F_{sync}, which adds additional sources of energy consumption ($e_{tx,sync}$ and $e_{rx,sync}$).

The times required for transmitting, receiving, overhearing, and synchronization in T-MAC are:

$$
\begin{aligned}
T^i_{\text{tx}} &= \frac{T_{\text{CW}}}{2} + T_{\text{RTS}} + T_{\text{SIFS}} + T_{\text{CTS}} + T_{\text{SIFS}} + T^i_{\text{msg}}, \\
T^i_{\text{rx}} &= \frac{T_{\text{CW}}}{2} + T_{\text{RTS}} + T_{\text{SIFS}} + T_{\text{CTS}} + T_{\text{SIFS}} + T^i_{\text{msg}}, \\
T_{\text{ov}} &= \frac{T_{\text{CW}}}{2} + T_{\text{RTS}}, \\
T_{\text{tx,sync}} &= \frac{T_{\text{CW}}}{2} + T_{\text{hdr}}, \\
T_{\text{rx,sync}} &= \frac{T_{\text{CW}}}{2} + T_{\text{hdr}}.
\end{aligned} \tag{4.45}
$$

Then, after each transmission or reception, a node stays idle for a period T_{idl} until the time-out timer expires (see Fig. 4.4.1). It takes into account possible clock drifts from its neighbors as follows:

$$T_{\text{idl}} = T_{\text{guard}} + T_{\text{time-out}}, \tag{4.46}$$

where:

$$T_{\text{time-out}} = T_{\text{CW}} + T_{\text{RTS}} + T_{\text{SIFS}} + T_{\text{CTS}}, \tag{4.47}$$

$$T_{\text{guard}} = 4\theta T_{\text{sync}}. \tag{4.48}$$

The energy spent in each mode is:

$$\begin{aligned} e^{i}_{\mathrm{tx}} &= \left(\frac{T_{\mathrm{CW}}}{2} + 3T_{\mathrm{SIFS}} + T_{\mathrm{idl}}\right) P_{\mathrm{idl}} + \left(T_{\mathrm{RTS}} + \frac{P^{i}}{R}\right) P_{\mathrm{tx}} \\ &\quad + (T_{\mathrm{CTS}} + T_{\mathrm{ack}}) P_{\mathrm{rx}}, \end{aligned} \tag{4.49}$$

$$\begin{aligned} e^{i}_{\mathrm{rx}} &= \left(\frac{T_{\mathrm{CW}}}{2} + 3T_{\mathrm{SIFS}} + T_{\mathrm{idl}}\right) P_{\mathrm{idl}} + (T_{\mathrm{CTS}} + T_{\mathrm{ack}}) P_{\mathrm{tx}} \\ &\quad + \left(T_{\mathrm{RTS}} + \frac{P^{i}}{R}\right) P_{\mathrm{rx}}, \end{aligned} \tag{4.50}$$

$$e_{\mathrm{ov}} = \frac{T_{\mathrm{CW}}}{2} P_{\mathrm{idl}} + T_{\mathrm{RTS}} P_{\mathrm{rx}}, \tag{4.51}$$

$$e_{\mathrm{idl}} = T_{\mathrm{idl}} P_{\mathrm{idl}}, \tag{4.52}$$

$$e_{\mathrm{tx,sync}} = \frac{T_{\mathrm{CW}}}{2} P_{\mathrm{idl}} + T_{\mathrm{hdr}} P_{\mathrm{tx}}, \tag{4.53}$$

$$e_{\mathrm{rx,sync}} = C\frac{T_{\mathrm{CW}}}{2} P_{\mathrm{idl}} + C T_{\mathrm{hdr}} P_{\mathrm{rx}}, \tag{4.54}$$

$$e_{\mathrm{cs}} = 0, \tag{4.55}$$

and the total energy spent in the synchronization and being idle in T_{obs} are (note that the other states are calculated in a way similar to the one above in B-MAC):

$$E_{\mathrm{tx,sync}} = \left(F_{\mathrm{sync}} e_{\mathrm{tx,sync}}\right) T_{\mathrm{obs}}, \tag{4.56}$$

$$E_{\mathrm{rx,sync}} = \left(F_{\mathrm{sync}} e_{\mathrm{rx,sync}}\right) T_{\mathrm{obs}}, \tag{4.57}$$

$$E_{\mathrm{idl}} = \left(\frac{T_{\mathrm{obs}}}{T_{\mathrm{slot}}}\right) e_{\mathrm{idl}}, \tag{4.58}$$

$$E_{\mathrm{ctrl}} = E^{l}_{\mathrm{rx,sync}} + E^{l}_{\mathrm{tx,sync}} + E_{\mathrm{idl}}, \tag{4.59}$$

where T_{slot} denotes the active period schedule of each node in T-MAC.

The total energy consumption in T_{obs} is:

$$E^{d,l}_{T_{\mathrm{obs}}} = E^{l}_{\mathrm{s}} + E^{d,l}_{\mathrm{tx}} + E^{d,l}_{\mathrm{rx}} + E^{d,l}_{\mathrm{ov}} + E_{\mathrm{ctrl}}. \tag{4.60}$$

Table 4.4.2: Parameters of the considered globally-synchronous MAC protocols and their values (used in Sections 4.4 and 4.5).

	Parameter	Description	Value
L-MAC	N_{slots}	Number of slots	32
TreeMAC	N_{slots}	Number of slots	3
	N_{frames}	Number of frames	[12, 20]
	T_{sync^*}	Synchronization message interval (s)	5
	T_{sch}	Schedule update interval (s)	8
	T_{bd}	Bandwidth demand update interval (s)	10

4.4.2 Globally Synchronized MAC Protocols

This class of MAC protocols uses topology information for scheduling the medium access in such a way that no two interfering nodes access the channel at the same time. This is achieved by assigning a unique time slot to each node. Thus, it can deliver a good performance when contention level is high. The time slot duration is predetermined and can hold a maximum amount of bytes. Every node can send a packet in its own slot only. In applications with predictable communication patterns, frame-slotted MAC protocols can achieve considerable energy savings by turning off the radio in slots where no messages will be received. For this reason, it is worth to evaluate their energy performance in low data rate WMSNs. In the following subsections we model the energy consumption of two frame-slotted MAC protocols: L-MAC and TreeMAC.

L-MAC

Lightweight MAC (L-MAC) [38] features a distributed TDMA scheme which organizes time into frames that are divided into N_{slots} slots (see Fig. 4.4.2). Each node can send a packet in its own slot and it performs carrier sensing in the remaining ones in order to check for incoming packets. A node has to wait a number of slots (N_{slots}-1) before being able to send the next packet. In every frame, C neighbors are sending a guarded header to mark their occupancy that is overheard by the given node. The parameters used in L-MAC are given in Table 4.2.1 and 4.4.2.

The time required to transmit, receive and overhear a packet of class i in L-MAC is:

$$\begin{aligned}
T^i_{\text{tx}} &= T_{\text{guard}} + T_{\text{hdr}} + \frac{P^i}{R}, \\
T^i_{\text{rx}} &= \frac{P^i}{R}, \\
T_{\text{ov}} &= C\left(\frac{T_{\text{guard}}}{2} + T_{hdr}\right), \\
T_{\text{cs}} &= (N_{\text{slots}} - 1)T_{\text{cs}},
\end{aligned} \tag{4.61}$$

respectively, where the guard time is given as follows:

$$T_{\text{guard}} = 4\theta T_{\text{frame}}, \text{ where } T_{\text{frame}} = N_{\text{slots}} T_{\text{slot}}.$$

The energy spent in each mode in a T_{frame} is:

$$e^i_{\text{tx}} = T_{\text{guard}} P_{\text{idl}} + \left(T_{\text{hdr}} + \frac{P^i}{R}\right) P_{\text{tx}}, \tag{4.62}$$

$$e^i_{\text{rx}} = \frac{P^i}{R} P_{\text{rx}}, \tag{4.63}$$

$$e_{\text{ov}} = C\left(\frac{T_{\text{guard}}}{2} + T_{\text{hdr}}\right) P_{\text{rx}}, \tag{4.64}$$

$$e_{\text{cs}} = ((N_{\text{slots}} - 1)T_{\text{cs}}) P_{\text{idl}}, \tag{4.65}$$

$$e_{\text{ctrl}} = 0, \tag{4.66}$$

and the total energy spent in overhearing and carrier sensing in T_{obs} are (note that the other states are calculated in a similar way to the one in B-MAC):

$$E_{\text{ov}} = \left(\frac{T_{\text{obs}}}{T_{\text{frame}}}\right) e_{\text{ov}}, \tag{4.67}$$

$$E_{\text{cs}} = \left(\frac{T_{\text{obs}}}{T_{\text{frame}}}\right) e_{\text{cs}}. \tag{4.68}$$

In a similar way, the total energy consumption in L-MAC in T_{obs} is:

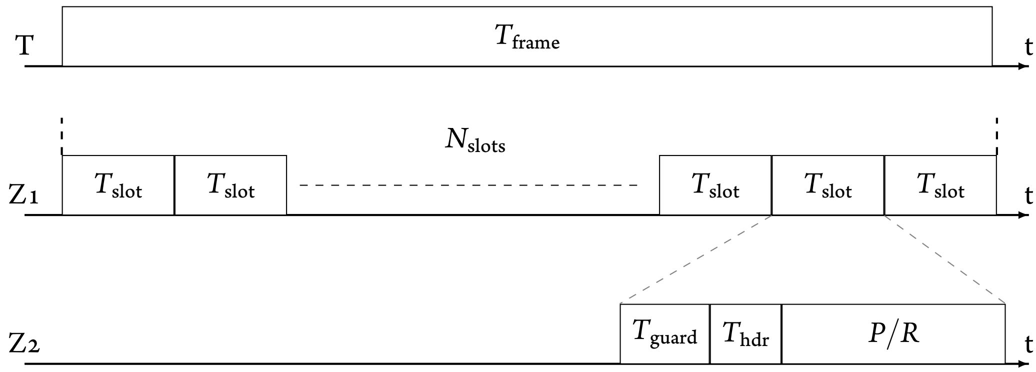


Figure 4.4.2: L-MAC.

$$E^{d,l}_{T_{\text{obs}}} = E^{l}_{\text{s}} + E^{d,l}_{\text{tx}} + E^{d,l}_{\text{rx}} + E_{\text{ov}} + E_{\text{cs}}. \tag{4.69}$$

TreeMAC

Based on the idea that equal channel access is not fair in the data collection scenario where nodes close to the sink need to forward more data than nodes further away, TreeMAC [39] allows every node to get a number of time slots proportional to its output traffic rate. Such a mechanism is suitable for the network topology mentioned and used in this study. TreeMAC divides each cycle into N_{frames} frames and each frame into three slots (see Fig. 4.4.3). By making use of the parent-children relationship, the frame-slot assignment is locally determined and exchanged between parent and children only. A parent determines children frames assignment based on their relative bandwidth demands, and each node calculates the slot assignment based on its hop-count to the sink. Using three slots, a node can avoid contention with its previous and next hop. Different from other TDMA-based MAC protocols, the frame-slot assignment in TreeMAC is a two-dimensional conflict-free sending/receiving and snooping. The frame assignment eliminates the horizontal two-hop interference. The slot assignment eliminates the vertical one. Given any node, at any time slot, there is at most one active sender in its 1-hop neighborhood (including itself). Each node wakes up in its assigned frames. In its sending slot, it sends the actual payload. In the receiving slot, it performs carrier sensing. TreeMAC requires nodes to update their bandwidth de-

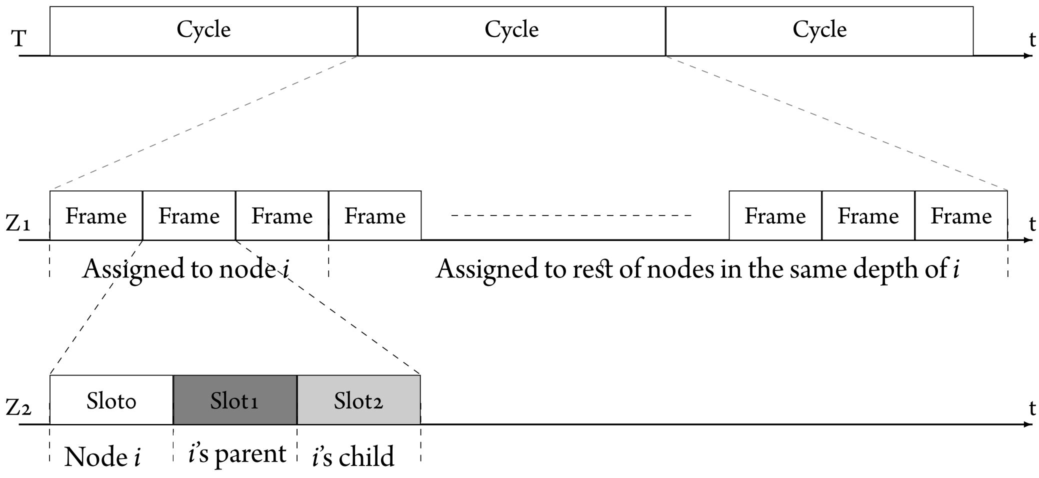


Figure 4.4.3: TreeMAC.

mand T_{bd}, and to send synchronization messages T_{sync*} and schedule updates T_{sch} periodically at different rates. The parameters of TreeMAC are given in Table 4.2.1 and 4.4.2.

The time required to transmit, receive and overhear a packet of class i in Tree-MAC is:

$$\begin{aligned}
T^{i}_{\text{tx}} &= T_{\text{guard}} + T_{\text{cs}} + T_{\text{hdr}} + \frac{P^{i}}{R}, \\
T^{i}_{\text{rx}} &= \frac{P^{i}}{R}, \\
T_{\text{ov}} &= 2\left(\frac{T_{\text{guard}}}{2} + T_{hdr}\right), \\
T_{\text{cs}} &= T_{\text{cs}}, \qquad (4.70)
\end{aligned}$$

respectively. We note that in TreeMAC, a given node overhears only its parent and child in its assigned frames which illustrates why the overhearing time is multiplied by two. In the other frames the node goes back to sleep. It senses the channel in its sending and receiving slots (i.e., when a packet can be received from its child). The guard time in TreeMAC is:

$$T_{\text{guard}} = 4\theta T_{\text{cycle}}.$$

The energy spent in each mode in a T_{frame} is:

$$e^i_{\text{tx}} = (T_{\text{guard}} + T_{\text{cs}})P_{\text{idl}} + \left(T_{\text{hdr}} + \frac{P^i}{R}\right) P_{\text{tx}}, \tag{4.71}$$

$$e^i_{\text{rx}} = \left(T_{\text{hdr}} + \frac{P^i}{R}\right) P_{\text{rx}}, \tag{4.72}$$

$$e_{\text{ov}} = 2\left(\frac{T_{\text{guard}}}{2} + T_{\text{hdr}}\right) P_{\text{rx}}, \tag{4.73}$$

$$e_{\text{cs}} = T_{\text{cs}} P_{\text{idl}}, \tag{4.74}$$

and the total energy spent in overhearing and carrier sensing in T_{obs} are derived by multiplying the energy spent in each mode, in one frame, by the number of frames assigned to the node in each cycle, and the number of cycles in T_{obs}. It is calculated as follows:

$$E_{\text{ov}} = \left(\frac{N_{\text{frames}}}{N_d}\right)\left(\frac{T_{\text{obs}}}{T_{\text{cycle}}}\right) e_{\text{ov}}, \tag{4.75}$$

$$E_{\text{cs}} = \left(\frac{N_{\text{frames}}}{N_d}\right)\left(\frac{T_{\text{obs}}}{T_{\text{cycle}}}\right) e_{\text{cs}}, \tag{4.76}$$

where N_d is the average number of nodes in ring d. Since we are placing nodes strategically in multiple rings, all nodes in the same ring will get an equal number of frames.

The energy spent in synchronization, scheduling, and bandwidth demand updates are:

$$e_{\text{sync}^*} = T_{\text{hdr}} P_{\text{tx}} + T_{\text{hdr}} P_{\text{rx}}, \tag{4.77}$$

$$e_{\text{sch}} = T_{\text{sch}} P_{\text{tx}} + T_{\text{sch}} P_{\text{rx}}, \tag{4.78}$$

$$e_{\text{bd}} = T_{\text{bd}} P_{\text{tx}} + T_{\text{bd}} P_{\text{rx}}, \tag{4.79}$$

and the total energy spent in each mode in T_{obs} is:

$$E_{\text{sync}^*} = \left(F_{\text{sync}^*} e_{\text{sync}^*}\right) T_{\text{obs}}, \tag{4.80}$$

$$E_{\text{sch}} = \left(F_{\text{sch}} e_{\text{sch}}\right) T_{\text{obs}}, \tag{4.81}$$

$$E_{\text{bd}} = \left(F_{\text{bd}} e_{\text{bd}}\right) T_{\text{obs}}, \tag{4.82}$$

$$E_{\text{ctrl}} = E_{\text{sync}^*} + E_{\text{sch}} + E_{\text{bd}}. \tag{4.83}$$

The total energy consumption in TreeMAC in T_{obs} is:

$$E^{d,l}_{T_{\text{obs}}} = E^{l}_{\text{s}} + E^{d,l}_{\text{tx}} + E^{d,l}_{\text{rx}} + E_{\text{ov}} + E_{\text{cs}} + E_{\text{ctrl}}. \tag{4.84}$$

4.5 Numerical Evaluation

In this section, we conduct a numerical evaluation of the energy consumption of the MAC protocols using the developed multi-class traffic model presented in Section 4.2 and the energy models in Sections 4.3 and 4.4. First, we start by investigating the traffic load conditions in each MAC protocol, which must be added to the network in order to make collisions negligible. Then, we illustrate how those conditions are tightly related to the sampling rates of nodes, the size of multimedia samples, and some network topology parameters such as the number of rings, the number of nodes in each ring and the density of MMSs. After that, we investigate the energy consumption of the MAC protocols under those traffic load conditions.

The topology considered in the numerical evaluation is a multi-ring topology (D, C), where we have L=2 classes of sensors, MMSs -with density p_m- that sample the environment at a rate F_s^{mms}, and SSs that sample the environment at a rate F_s^{ss}. The size of the captured image depends on the phenomena being monitored. Except where otherwise stated, we assume an image size of 10KB and a multimedia payload of size P=512B which gives us M=20 payloads per image.

4.5.1 Parameters constraints

In order to make collisions negligible, we present some safeguarding conditions on the amount of traffic flowing through the network against any improper selection of MACs parameters. It is worth noting that each category of MAC protocols has a different traffic boundary condition according to its medium access strategy. However, in all MAC protocols this will be done by adding the condition to the busiest nodes in the network, which have the most packets to send (i.e., nodes close to the sink in ring d=1). The constraints below are derived in a similar way as in [30], and the thresholds are assumed to be the same.

In the case of asynchronous MAC protocols, we derive a general condition which guarantees that the maximum traffic load transmitted by all nodes in d=1, of any class l, to the sink (in d=0) does not exceed 25% of the channel bandwidth. This can be described by the following equation:

$$\sum_{l}^{L} I_{0}^{l} F_{\text{out}}^{1,l} M^{l} T_{\text{tx}} < \frac{1}{4}, \tag{4.85}$$

where I_{0}^{l} is the sink's average number of input links of class l. This condition can be adapted to each asynchronous MAC protocol according to the packet transmission time T_{tx} of each one.

In the case of locally synchronized MAC protocols, such as T-MAC, the total traffic transmitted by all nodes in d=1 during the active period (T_{slot}) should not exceed 25% of the channel bandwidth. This can be described as follows:

$$\sum_{l}^{L} I_{0}^{l} F_{\text{out}}^{1,l} M^{l} T_{\text{slot}} < \frac{1}{4}. \tag{4.86}$$

In globally synchronized MAC protocols, collisions is avoided since every node has a unique transmission slot. However, we set a bound on the maximum traffic transmitted by bottleneck nodes in d=1 in order to avoid long queuing delays.

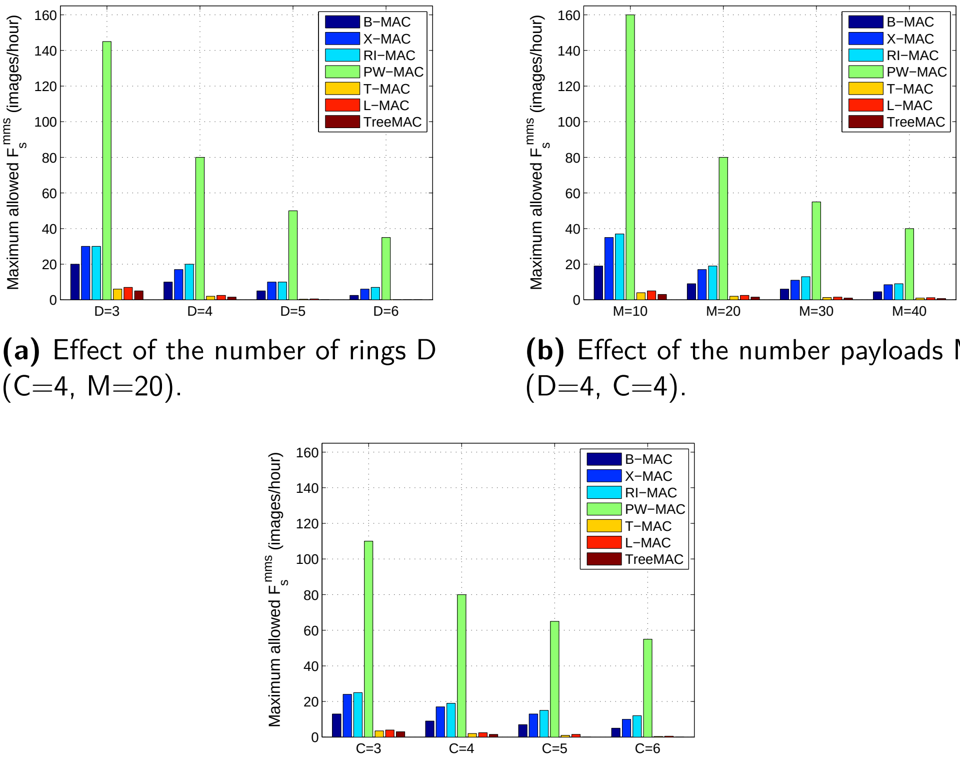
In L-MAC we have:

$$\sum_{l}^{L} I_{0}^{l} F_{\text{out}}^{1,l} M^{l} T_{\text{frame}} < \frac{1}{2}. \tag{4.87}$$

In the case of TreeMAC, the threshold is calculated as follows:

$$\sum_{l}^{L} I_{0}^{l} F_{\text{out}}^{1,l} M^{l} T_{\text{cycle}} < \frac{1}{2}. \tag{4.88}$$

Setting a bound on the amount of traffic flowing through the network implies that the sampling rate of MMSs can not be increased more than a certain value. This also imposes other constraints on some network topology parameters such as the number of rings, the number of nodes in each ring, and the density of MMSs, because the output traffic increases by increasing those parameters. In Fig. 4.5.1, we show how the network topology parameters and the size of multimedia sample directly affect the maximum value of MMSs' sampling rate (F_{s}^{mms}) allowed for each MAC protocol in order to make collisions negligible. This is calculated based on the aggregated output traffic sent



(a) Effect of the number of rings D (C=4, M=20).

(b) Effect of the number payloads M (D=4, C=4).

(c) Effect of the number of nodes in the first ring C (D=4, M=20).

Figure 4.5.1: The effect of network parameters and the size of the multimedia sample on the maximum allowed sampling rate of MMSs (F_s^{mms}).

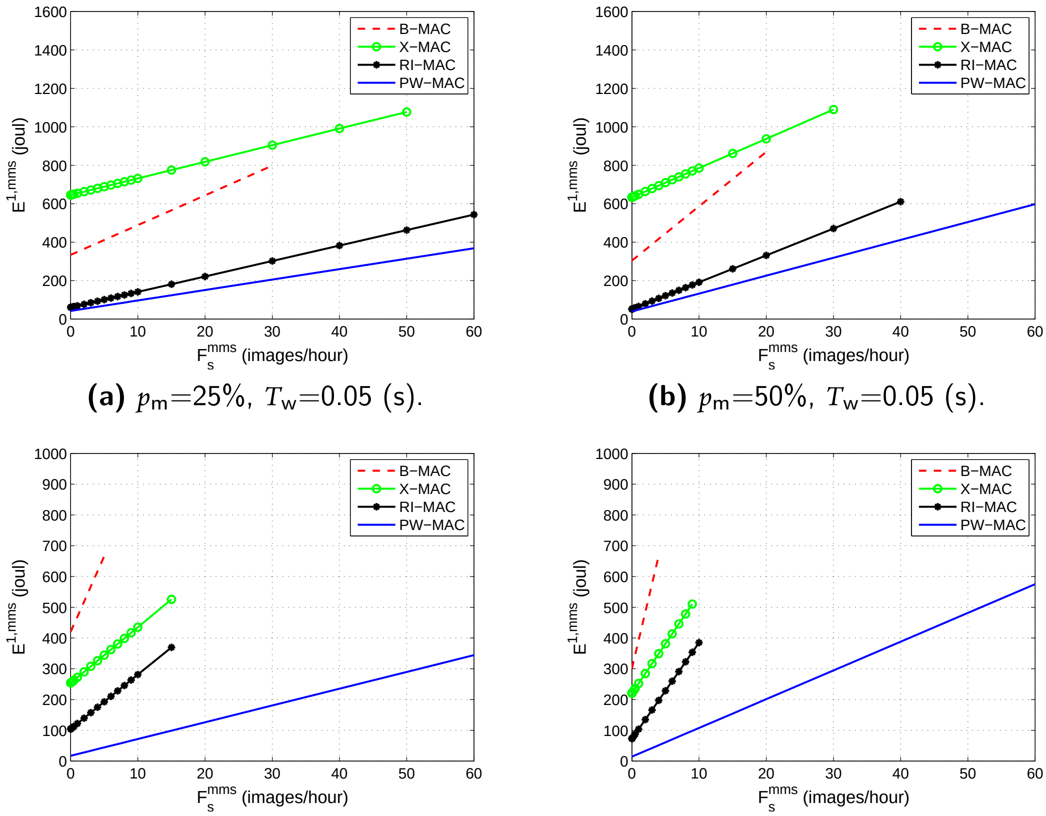
by all busy nodes in ring d=1 satisfying the conditions above. In Fig. 4.5.1, we assume that SSs sample the environment at a fixed sampling rate F_s^{ss}=60 (samples/hour) and that the density of MMSs is constant p_{m}=50%. For instance, Fig. 4.5.1 (a) shows that we can not increase F_s^{mms} in B-MAC more than 20 (samples/hour) when D=3, while it is possible to increase F_s^{mms} in PW-MAC up to 145 (samples/hour) under the same network configurations and size of the multimedia sample. On the other hand, Fig. 4.5.1 show that under the same configurations (i.e., F_s^{ss}=60 (samples/hour) and p_{m}=50%) synchronous MAC protocols can not be used in a network with more than D=4 rings or more than C=4 nodes in the first ring, and the maximum allowed F_s^{mms} in the best scenario does not exceed 6, 7 and 5 (samples/hour) for T-MAC, L-MAC and TreeMAC, respectively, when D=3. Hence, it can be inferred from the figure that asynchronous MAC protocols give better flexibility to the range of allowed sampling rates than synchronous MAC protocols for different network configurations. In particular, PW-MAC allows MMSs to sampling the environment at relatively high rates.

4.5.2 Parameters study

In this section, the energy consumption of the MAC protocols is evaluated. First, we investigate the energy consumption of sender-initiated MAC protocols (B-MAC and X-MAC) and receiver-initiated MAC protocols (RI-MAC and PW-MAC). Then, we analyze the energy consumption of synchronous MAC protocols from the two categories: i) locally synchronized (T-MAC), and ii) globally synchronized (L-MAC and TreeMAC). Finally, we compare the different categories of MAC protocols, and recommend the network settings and MAC parameters suitable for each MAC protocol. The topology considered in this experiment is a multi-ring topology (D=4, C=4), resulting in a network of 64 nodes. Our goal is to assess the energy consumption of the MAC protocols under different values of F_s^{mms}, polling time intervals T_{w} (i.e., in case of asynchronous MACs), and densities of MMSs p_{m}.

We focus our attention on the energy consumption of nodes close to sink (i.e., in ring d=1) since these nodes always have more traffic to send/receive than all other nodes. A node in ring d=1 has to convey its own traffic plus the whole traffic from outer rings. The traffic and radio parameters, as well as the specific parameters for all the MAC protocols are provided in Tables 4.2.1, 4.3.2, 4.3.1, 4.3.3, 4.4.1 and 4.4.2. The radio parameters are taken from the datasheet of MICAz platform [214] and the Chipcon CC2420 radio [215].

Fig. 4.5.2 compares the energy consumption of the selected asynchronous MAC protocols in a WMSN with sampling rates F_s^{ss}=60 (samples/hour) and F_s^{mms} in the interval [1/96,60] (images/hour), and for two different polling period (T_{w}) values: 0.05 and 0.2 seconds. Based on the parameter constraints presented in Section 4.5.1, the energy consumption of each MAC protocols is only plotted in its allowed interval of F_s^{mms}. From Fig. 4.5.2, it can be noticed that in the entire allowed sampling rate interval and for short and long polling periods, the energy consumption of receiver-initiated MAC protocols (i.e., RI-MAC and PW-MAC) is always lower than the sender-initiated ones (i.e., B-MAC, X-MAC). This is because the sender-initiated MAC protocols adopt the duty cycling technique where a node sends a long preamble to ensure communication with its intended receiver. This long preamble is a source of energy consumption in sending, receiving and



(a) $p_{\rm m}$=25%, $T_{\rm w}$=0.05 (s).

(b) $p_{\rm m}$=50%, $T_{\rm w}$=0.05 (s).

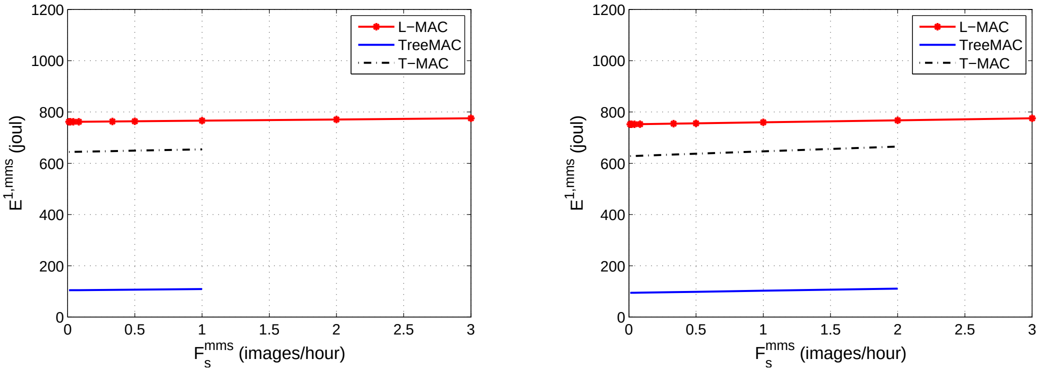
(c) $p_{\rm m}$=25%, $T_{\rm w}$=0.2 (s).

(d) $p_{\rm m}$=50%, $T_{\rm w}$=0.2 (s).

Figure 4.5.2: The energy consumption of B-MAC, X-MAC, RI-MAC and PW-MAC during $T_{\rm obs} = 24$ (hour) in a WMSNs of 64 Nodes and for different polling periods and densities of MMSs.

overhearing (see Section 4.3). Besides, it results in a longer transmission time ($T_{\rm tx}$) which limits the maximum allowed sampling rate of MMSs (see Eq. 4.85). In receiver-initiated MAC protocols, the time during which a sender and its intended receiver are occupying the channel to be able to communicate is reduced, and a sending node does not start transmitting until the receiver is ready to receive. In PW-MAC, a sender wakes up just before its intended receiver which illustrates why PW-MAC consumes the least amount of energy between the asynchronous MACs. This mechanism of PW-MAC also reduces the transmission time of the sender ($T_{\rm tx}$) and allows for a wider range of $F_s^{\rm mms}$.

At very low sampling rates, B-MAC achieves lower energy consumption than X-MAC when the polling period $T_{\rm w}$ is short (Fig. 4.5.2(a) and Fig. 4.5.2(b)). This is because X-MAC has a longer



(a) p_{m}=25%.

(b) p_{m}=50%.

Figure 4.5.3: The energy consumption of L-MAC, TreeMAC and T-MAC during an observation time $T_{\mathrm{obs}} = 24$ (hour) in a WMSNs of 64 Nodes and for different densities of MMSs. At F_s^{mms}= 2 (images/hour), when p_{m}=25 % we have in total 3520 (packets/hour) which causes Eq. (88) in TreeMAC, for instance, to be higher than 50%, but when p_{m}=50 % we have 3200 (packets/hour) and the condition is fulfilled.

carrier sensing period ($T_{\mathrm{cs}} + T_{\mathrm{ea}}$), and since the polling period is short, nodes have to wake up and perform carrier sensing more often, and as consequence more energy is consumed. However, nodes in B-MAC consume the largest amount of energy as the polling period (T_{w}) gets longer and/or the sampling rate increases. At higher sampling rates, the generated traffic is higher and the carrier sensing is less frequent. In these cases, X-MAC outperforms B-MAC since it uses short preamble bursts which reduces the preamble length to the half on average.

The effect of the density of MMSs p_{m} on the energy consumption of MACs (i.e., p_{m}=0.25 and p_{m}=0.5) is also presented in Fig. 4.5.2. In both cases, B-MAC still outperforms X-MAC at low sampling rates when the polling period is short. It can be observed that in the four mentioned scenarios, receiver-initiated MAC protocols have better energy performance and allow for a wider range of sampling rates. In particular, PW-MAC allows MMSs to sample the environment at F_s^{mms} up to 80 (images/hour) under the same network configuration (i.e., C=4, D=4, M=20, and F_s^{ss}=60 (samples/hour)) and when the density of MMSs p_{m} is 50% (see Fig. 4.5.1 (a)).

In Fig. 4.5.3, we compare the energy consumption of the synchronous MAC protocols modeled in Sections 4.4. We use the same network configurations as in the previous experiments except that in these protocols it is not allowed to increase F_s^{mms} more than 3 (images/hour), otherwise the traffic load constraints at the bottleneck nodes can not be satisfied (see Section 4.5.1). This is because

Table 4.5.1: The recommended MAC protocols for each scenario.

	Asynchronous				Synchronous		
	Receiver-initiated		Sender-initiated				
	B-MAC	X-MAC	RI-MAC	PW-MAC	T-MAC	L-MAC	TreeMAC
Very low sampling rate F_s^{mms}	✓		✓	✓			✓
Low sampling rate F_s^{mms}		✓	✓	✓			
Low density of MMSs	✓	✓	✓	✓			✓
High density of MMSs		✓	✓	✓			✓
Long polling period				✓	-	-	-
Short polling period	✓		✓	✓	-	-	-

the longer duration of T_{slot}, T_{frame}, and T_{cycle}, in T-MAC, L-MAC and TreeMAC, respectively, than T_{x} in asynchronous MAC protocols. From this figure, we notice that for different densities of MMSs, L-MAC and T-MAC consume higher energy than TreeMAC. A node in L-MAC needs to sense the channel in each slot -except the one it owns- during the whole observation time (T_{obs}=24 hours), which is the major source of energy consumption in L-MAC. In T-MAC, a huge amount of energy is spent in the idle mode during T_{obs}. On the contrary, TreeMAC achieves a lower energy consumption since it has a predetermined structure of frames/slots assigned to nodes. Nodes wake up only in their assigned frames without the need of carrier sensing in each frame/slot. Besides, this structure limits overhearing to the assigned frames/slots only, which also helps in reducing the energy consumption. In synchronous MACs there is no need for polling/sensing the channel or sending beacons periodically. However, this comes at the cost of an extra synchronization overhead and a very limited allowed range of sampling rates. Therefore, the usage of these protocols is limited to WMSNs working at very low data rates.

Fig. 4.5.3 also shows that for a higher density of MMSs (p_{m}= 50%), the sampling rate of MMSs (F_s^{mms}) can be increased in T-MAC and TreeMAC up to 2 (images/hour). The reason is that the sampling rate of SSs (F_s^{ss}) is constant and set to be 60 (samples/hour). Thus, at very low data rate of MMSs, the output traffic generated from SSs is higher than MMSs. Therefor, when p_{m} is low the total output traffic generated at bottleneck nodes is higher and it decreases as the density of MMSs increases.

Table 4.5.1 overviews the scenarios in which each MAC protocol is recommended. It can be concluded that receiver-imitated MAC protocols are suitable for this type of networks, allowing for a wider range of sampling rates, while in synchronous MAC protocols only TreeMAC is recommended and for WMSNs with very low sampling rates.

4.5.3 Application scenarios

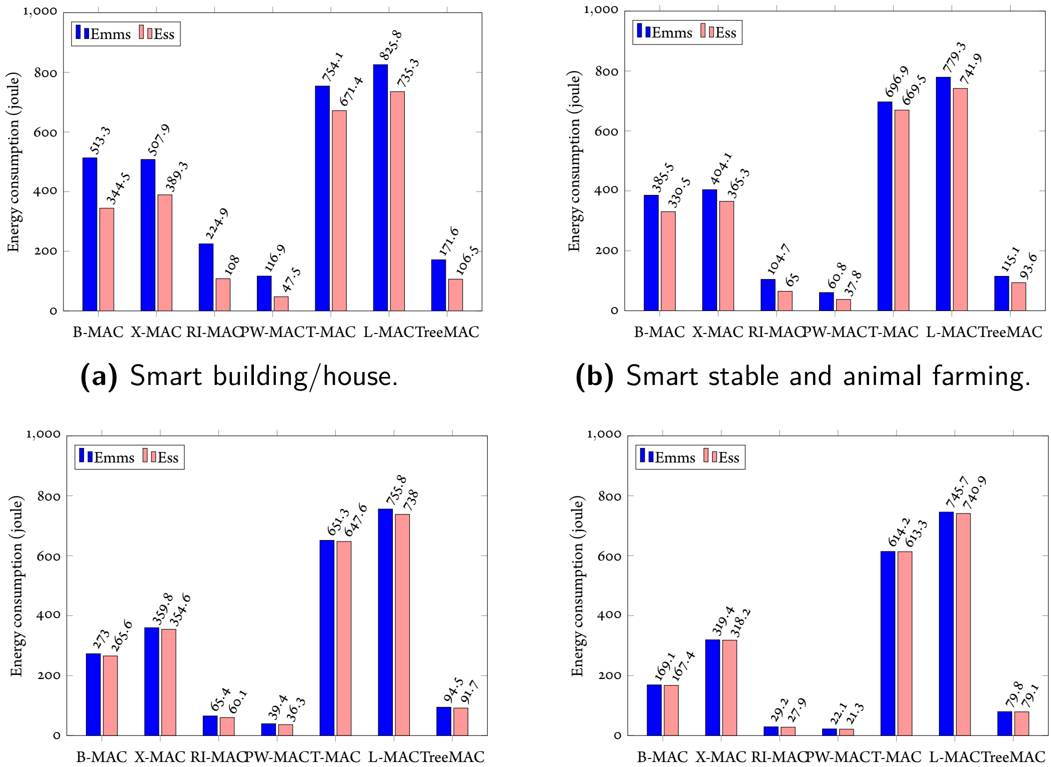
In this section we use the multi-class traffic model to assess the performance of MAC protocols in different WMSNs application scenarios related to smart cities. We distinguish between two groups of application scenarios: i) indoor scenarios such as smart houses/buildings, and stables, and ii) outdoor scenarios such as urban resilience applications and smart farms/gardens. In each scenario, we integrate two types of sensors (i.e., multimedia and scalar) each with a different sampling rate. The configurations of the selected WMSN in each application are listed in Table 4.5.2 and the MAC protocols under these configurations have been verified to satisfy the traffic load conditions in Section 4.5.1. The energy consumption of MAC protocols in each application is shown in Fig. 4.5.4.

Indoor applications

In indoor applications, such as smart buildings/houses, various type of sensors and electronic devices are interconnected through a communication network to monitor and control remotely different phenomenons inside the place such as temperature and humidity, lighting, occupancy and movement, kids, plants and pets situation, products and warehouses in shopping centers, among others. In the following subsection, we consider two application scenarios that deploy low data rate WMSNs.

Smart building/house Intelligent buildings, including smart homes and office spaces, have been extensively studied in the literature [216–220]. All of these projects and studies make extensive use of sensors to monitor objects and spaces inside and around the house/building giving inhabitants the ability to remotely control them. In this scenario, we deploy a WMSN with 16 sensors arranged in D=2 rings and each node with C=4 neighbors.

Smart stable and animal farming We deploy a WMSN of 24 (D=2, C=6) sensors to remotely monitor animals in a stable and in a small animal farm. SSs can monitor the temperature, humidity, door and window open/close status, among others, while MMSs periodically send images about the animals' situation inside and around the stable. In particular, deploying such a WMSN to monitor the animals' situation can help prevent illness and theft, and allows the farmer to remotely keep an eye on the animals during days and nights (e.g., the sensor network deployed for



(a) Smart building/house.

(b) Smart stable and animal farming.

(c) Urban/territorial resilience.

(d) Smart agriculture.

Figure 4.5.4: The energy consumption of MAC protocols in the selected indoor and outdoor application scenarios.

monitoring horses and equine farm management in [221, 222]).

Outdoor applications

In this type of applications we consider some applications for low data rate WMSNs where the multimedia and scalar sensors can be deployed together to monitor and control different phenomenons in the city/territory such as structural health (e.g., buildings, bridges and historical monuments), noise and sound monitoring in bar zones and centric areas, rivers and dams situation, ambient control, among others. Outdoor applications also includes smart farms/gardens.

Urban/territorial resilience As we mentioned above, WMSNs can be deployed in urban management systems to monitor and observe the territory, and prevent the disruption of essential

Table 4.5.2: The configurations of the WMSN of each scenario (M=20 and T_w= 0.1 (s) in all scenarios).

	Number of sensors	Density of MMSs	Sampling frequency (samples/hour)	
	N	p_m	F_s^{ss}	F_s^{mms}
Smart building/house	16	20%	60	30
Smart stable and animal farming	24	40%	30	15
Urban/territorial resilience	80	60%	4	2
Smart agriculture	150	30%	2	0.5

city services (e.g., La Garrotxa Urban Resilience project in Catalunya [223]). In this scenario we deploy a WMSN of 80 sensors (D=4, C=5). Since the phenomenas being monitored (e.g., noise and sounds, ambient control, structural health, among others) are non-time critical, we choose low sampling rates for both SSs and MMSs (see Table 4.5.2).

Smart farm and agriculture The use of sensor networks in smart agriculture [224] is very promising as multiple environmental parameters can be monitored. This includes a wide range of applications, from crops status and growing conditions analysis to weather observation, such as vineyards, tropical fruits and herbs that are sensitive to cold, where a slight change in climate can affect the final outcome. All of this information can also help to determine the optimum conditions for crops, by keeping an archive of images and comparing them with the figures and images obtained during the best harvests, which leads to better productivity, costs reduction, and improved management (e.g., the Rias Baixas Smart Viticulture project in Galicia [225]). In this scenario we deploy a WMSN of 150 (D=5, C=6) sensors with very low sampling rates.

Discussion

From Fig. 4.5.4 we can see that in all the selected scenarios, PW-MAC, RI-MAC and TreeMAC show a low energy consumption performance for both types of sensors. On the contrary, L-MAC and T-MAC consume the highest amount of energy and they are not recommended for this kind of networks and applications. In sender-initiated asynchronous MAC protocols, X-MAC has a better energy performance than B-MAC in smart buildings/house applications since the sampling rates in these applications are comparatively high (F_s^{ss}= 60, F_s^{mms}=30 (samples/hour)). In the mentioned outdoor applications, sensors sample the environment at very low sampling rates which illustrates why B-MAC has a close energy consumption performance to X-MAC.

4.6 Conclusions

In this study we derived a multi-class traffic model and used it to analyze the energy consumption of some recent and baseline MAC protocols in low data rate delay-tolerant WMSNs. We modeled the energy consumption of MAC protocols from different categories including asynchronous (sender-initiated and receiver-initiated), and synchronous (locally and globally) MAC protocols. The derived models allow us to compare the performance of MAC protocols as a function of the network topology, the density of multimedia nodes and the sampling rates.

From the numerical analysis, it is noticed that in the asynchronous MAC protocols category, receiver-initiated MAC protocols outperform sender-initiated ones. In particular, PW-MAC shows the lowest energy consumption between the selected asynchronous MAC protocols and it can be used in WMSNs with a wide range of sampling rates. Regarding synchronous MAC protocols, results also show that they are only suitable for WMSNs when the data rates are very low. In that situation, TreeMAC is the one that offers a lower energy consumption.

From the application scenarios we studied, it can be observed that some of the existing MAC protocols in WSNs are suitable for non-streaming non-time critical WMSNs without the need for additional control mechanisms like streaming and QoS-aware MAC protocols. However the selection of the MAC protocol and its parameters strongly depends on the application scenario.

To conclude, this study offers a mathematical modeling and a numerical evaluation of MAC protocols in WMSNs that we believe it fills a need in the current literature and gives researchers a very clear view of the energy consumption of some recent MAC protocols in low data rate WMSNs and their application scenarios. Having these models and results may enable future research efforts to improve upon the energy efficiency of the current MAC protocols, and help users to choose the most adequate one for each scenario.

5

A Distributed Energy Sharing Framework among Households in Microgrids based on a Repeated Game Approach

5.1 Introduction

In this chapter, we assess the economical and environmental potential of a proposed distributed energy sharing framework for microgrids, where households can cooperate and share their surplus renewable energy in an intelligent and harmonized manner. Households satisfy their demand from their DERs first and if they have surplus renewable energy, they can share it with a neighboring household. The economical potential is expressed as electricity demand cost savings and the environmental potential is expressed as CO_2 emissions reduction per kWh of electricity demand. We use a repeated game approach to model the interaction between rational households. In repeated games, in contrast to one-shot games (see Chapter 2), players interact with each other for multiple rounds, and in each round they play the same game. In such situations, players have opportunities to adapt to their opponents' behavior (i.e., learn) and try to become more successful, which is very useful in our proposed distributed energy sharing framework. We prove that a Sub-game Perfect Nash Equilibrium (SPE) exists and can be sustained if households are sufficiently patient. Algorithms that support households in running the game and finding the best matching household in a distributed manner are also presented. Numerical analysis presented in this work are based on real data of renewable energy profiles, electricity pricing, and demand profiles for households of different sizes and consumption patterns and in different annual periods. Results show that households are able to reduce their demand costs if they share their renewable energy and play in a cooperative manner.

This chapter is structured as follows. System model is illustrated in Section 5.2. The proposed repeated game model is described and analyzed in Section 5.3. In Section 5.4, the distributed energy sharing algorithm is presented. Numerical results are discussed in Section 5.5. Finally, we conclude the chapter and give pointers for possible future directions in Section 5.6.

Part of the work presented in this chapter has been published in [226], extended later and submitted to [227].

5.2 System Model

In this study we consider a generic microgrid which consists of a set of households $\mathcal{N} = \{1, \ldots, N\}$, where $N = |\mathcal{N}|$, with a small-scale on-site DER (e.g., a solar PV panel). Households are connected to each other and to the main grid via AC power lines. Further, it is assumed that households' power demands might be variable both in quantity and time and that they can approximately predetermine their future demands. Time is divided into periods (e.g., days) and each time period is divided into slots (e.g., hours), which represent the time instants at which a certain event or an interaction may occur in the system (i.e., borrowing/lending a certain amount of energy).

In fact, households' electricity consumption patterns do not necessarily overlap with each other which can be exploited to minimize the need of purchasing electricity from the main grid. This can be achieved by allowing households to share their renewable energy in a cooperative fashion. At a certain time slot each household can be a power supplier and share some amount of its harvested renewable energy, and/or a demander which may request some amount of renewable energy from another household.

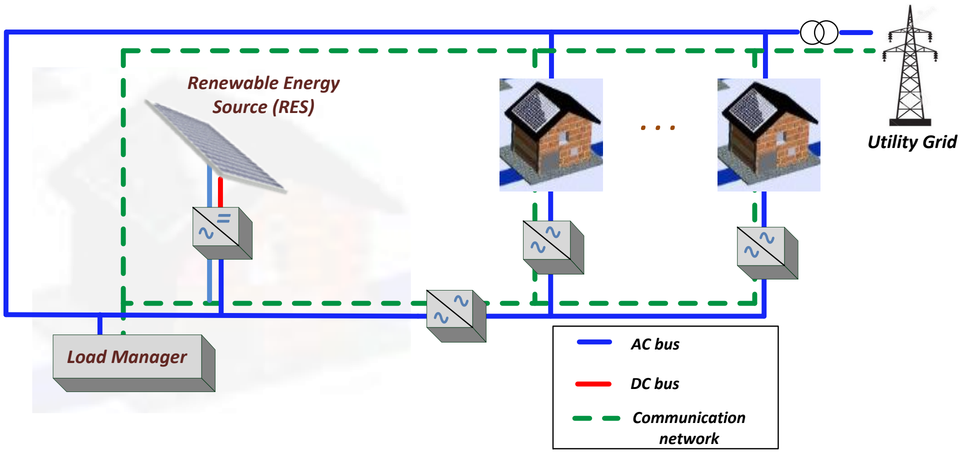


Figure 5.2.1: The proposed microgrid scheme (used in Chapter 5).

Further, the applied model assumes that each household is equipped with a smart energy meter, which monitors and controls energy harvesting and power consumption intelligently. SM are also responsible of data communication between households themselves and between households and the main grid. They exchange information about households' demands, available renewable energy and prices of energy at each time slot. The proposed system architecture is illustrated in Fig. 5.2.1.

Let $\mathcal{H} = \{1, \ldots, H\}$ denote the set of time slots. A power action of a household $i \in \mathcal{N}$ depends on a time slot $h \in \mathcal{H}$. At every time slot h, each household i has two values : i) an amount of renewable power S_i^h, generated by its on-site solar panel, and ii) an amount of power demand D_i^h, where $S_i^h, D_i^h \in \mathbb{R}$. From those values a household can determine at every h if an additional power demand is needed or if it has a surplus amount of renewable power. We assume that households satisfy their own demands first from their own on-site solar PV system and after that if an amount of renewable energy remains or if an additional demand is still needed, they can cooperate and borrow/lend each other. This is achieved by subtracting the renewable power value from the demand value as follows:

$$P_i^h = D_i^h - S_i^h \tag{5.1}$$

After a series of time slots, each household i will have a power vector P_i that indicates the additional demand as well as the surplus renewable power at each time slot h. This power vector is defined as $P_i = [P_i^1, P_i^2, \dots, P_i^H]$, where $P_i^h \in \mathbb{R}$.

Negative values of P_i indicate the required additional demand at the corresponding time slots, while positive ones represent the surplus renewable power that could be shared with other households. Then, each household will have two vectors that can exchange with other households: i) $\hat{D}_i = [\hat{D}_i^1, \hat{D}_i^2, \dots, \hat{D}_i^H]$ which contains the additional demand at each time slot $h \in \mathcal{H}$, and ii) $\hat{S}_i = [\hat{S}_i^1, \hat{S}_i^2, \dots, \hat{S}_i^H]$ which contains the surplus renewable power at each time slot $h \in \mathcal{H}$, where $\hat{S}_i^h, \hat{D}_i^h \in \mathbb{R}$. Each time slot can represent different timing horizons (e.g., an hour), where the relationship between P_i vector and $\hat{S}_i$ and $\hat{D}_i$ vectors can be described as follows:

$$P_i = \hat{D}_i + \hat{S}_i \tag{5.2}$$

5.3 Repeated Energy Sharing Game

5.3.1 Game Formulation

The energy sharing interaction among households in a microgrid is formulated using a discounted repeated game, proposed by [228]. Consider a finite normal form stage game denoted by tuple $\mathcal{G} = (\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}})$, where $\mathcal{N}$ is the set of players in the game composed of all end-consumers (i.e., households) in a microgrid community, $\mathcal{S}_i$ is the strategy space available for player $i \in \mathcal{N}$ and u_i is the utility function for player i. Households are playing the same stage game $\mathcal{G}$ repeatedly over time. In each stage, each household has the following available actions:

- **Cooperate (C):** Household i cooperates and shares an amount of its renewable energy with another household in the microgrid in order to increase its payoff.
- **Defect (D):** Household i stops playing and sharing its renewable energy with its opponent if the opponent defects or if a cost saving is not achieved.

The utility function u_i is the function used to calculate the economical payoff of household i from playing the game, capturing the benefit earned by sharing energy with other players. The household's cost for additional demand, that has to be purchased from the main grid, and the cost of its residual renewable energy are used to determine the benefit (i.e., cost savings and accompanied emissions reduction) earned by sharing energy. Those costs are considered to be the main factors of the utility function in this game. The utility function of household i is defined as:

$$u_i(s_i, s_{-i}) = \sum_{h\in\mathcal{H}} c_i^h \hat{D}_i^h - a_i^h \hat{S}_i^h \tag{5.3}$$

where c_i^h is the cost of purchasing one kWh from the main grid at time slot $h \in \mathcal{H}$. In case of cooperation, where a household receives a certain amount of renewable energy from neighboring households, its additional demand's cost is reduced (i.e., an implicit benefit is achieved). $\sum_{h\in\mathcal{H}} aS_i^h$ denotes the residual renewable energy cost at the end of each stage for household i, where a_i^h is a weighting coefficient measured in cents/kWh. This cost could be used as a metric in a monetary unit to express the value of residual renewable energy in household i at each time slot h.

The payoff vector is defined as $r = (r_1, \ldots, r_N)$, where $N = |\mathcal{N}|$, which represents the utility that the households receive in the game. Each player has a discount factor $0 < \beta_i < 1$ and it is assumed that this discount factor is the same for all households. $\mathcal{T} = \{1, \ldots, T\}$ denotes the finite history of length $T = |\mathcal{T}|$ that the repeated game is being played. The stage game is the game played at each time period $t \in \mathcal{T}$. The payoff of player i from playing a sequence of actions in history of length t (i.e., $s^1, \ldots, s^t, \ldots$) is given by the following discounted reward formula:

$$r_i = \sum_{t\in\mathcal{T}} \beta_i^t u_i(s^t) \tag{5.4}$$

There are two equivalent interpretations of the discount factor. One interpretation is that household i cares more about its demand cost reduction in the near future than in the long term. The other interpretation is that the household cares about the future just as much as the present, but with probability $(1 - \beta)$ the game may end in any given round.

5.3.2 Equilibrium Strategy Design

In the proposed repeated energy sharing game households are assumed to have patience and a long-term relationship to each other, which makes their strategic behavior different from that of a one-shot game. That means that they have a long-term plan to reduce their cost. Repeated play allows each player's move to be contingent on the opponent's prior move, and thus each household must consider the reactions of its opponent in making a decision. The fact that the game is repeated allows the players to agree on a certain sequence of actions and punish the players that deviate. The agreement among households is a set of rules to cooperate and lend/borrow each other some amount of renewable energy. If two households cooperate, their long term benefit of cooperation may outweigh the short-run temptation to defect. Thus, it can lead to a lower cost for all households in a long-term. The most dramatic expression of this phenomenon is the celebrated "Folk Theorem" [228, 229]. The Folk Theorem (Theorem 1) asserts that any feasible individually rational payoff can arise as a Nash equilibrium of the repeated games, if players are sufficiently patient.

Theorem 1 (Folk Theorem) *Consider a finite normal form game $\mathcal{G}$, let $s = (s_1, \ldots, s_N)$ be a Nash equilibrium of the stage game $\mathcal{G}$, and let $s' = (s'_1, \ldots, s'_N)$ be a feasible alternative strategy of $\mathcal{G}$ such that: $u_i(s') > u_i(s), \forall i \in \mathcal{N}$. There exists some discount factor β sufficiently close to 1, such that $\beta_i \geq \beta, \forall i \in \mathcal{N}$. Then there exists a SPE of the infinitely repeated game $\mathcal{G}(\beta)$ that has s' played in every period on the equilibrium path.*

According to Folk theorem, a household can play s' as long as its opponent has played s' in the past as well. If a household does not consider future and wants to maximize its utility at the current time slot by deviating and switching to a strategy s''_i, its opponent switches in the next time period, for a specified number of periods, to a strategy that minimizes the opponent's maximum payoff (i.e., to the strategy s). There are some famous punishment strategies in this case. One example is the strategy "Tit-for-tat" [230] in which players start out cooperating. If the households' opponent defected, the household defects in the next round. Then it goes back to cooperation. In contrast, in the "Grim Trigger" strategy [229] players start out cooperating. If the opponent ever defects, the households defects forever. However, it is proved [228, 229] that deviation is not beneficial if every player has a high enough discount factor β_i given by:

$$\beta_i \geq \frac{M}{M+m} \tag{5.5}$$

where M is the maximum gain from deviation and is calculated as follows:

$$M = \max_{i, s''_i} u_i(s''_i, s'_{-i}) - u_i(s') \tag{5.6}$$

and m is the minimum per-period loss from future punishment:

$$m = \min_i u_i(s') - u_i(s) \tag{5.7}$$

Algorithm 1 A distributed algorithm executed by N households.

1: For each household i calculate $\overline{\hat{D}}_i$ and $\overline{\hat{S}}_i$ in the past week
2: Calculate the Eculidean distance matrix d between the N households
3: Sort each row in d in a descending order
4: Run Gale-Shapley algorithm (Algorithm 2) to find the best matching households based on d.
5: Run the game between the selected pairs and repeat it for a certain number of time periods T (e.g., one week), and allow the selected pairs to play cooperate (C) in each stage
6: Calculate the payoff $r_i(s')$ after T
7: **if** $(r_i(s) < r_i(s'))$ or $(r_i(s') <$ threshold$)$ **then**
8:     Defect and leave the stage game
9: **else**
10:     Keep cooperating with the same pair in the following time periods
11: The defecting households and their corresponding pairs go to step 1

5.4 Distributed Algorithm

In Section 5.3, it is shown that a household would be willing to cooperate and borrow/lend some amount of energy from/to another household in the microgrid. In particular, we proved via Folk Theorem that a SPE exists and can be sustained if households are sufficiently patient (i.e., the discount factor β is sufficiently close to 1). In this section, Algorithm 1 is provided to be implemented in households' SM, that allows them to run the game and support their decisions in finding and selecting the best matching pair from a pool of households to play the stage game with. The proposed algorithm gives flexibility to any household to change its matching pair after a certain history according to some metrics (e.g., if a household' opponent defected or if the cost saving is less than a certain threshold). The strength of this algorithm can be summarized in three main points; i) it is fully distributed, ii) it can be applied in any microgrid scenario regardless of the size and power consumption pattern of participating households, and iii) it allows a fair matching between households.

Assume a set of households $\mathcal{N}$. Each household sets a list of preferences for households of which it prefers to play the game with. This is done based on the Eculidean distance between the household's average additional demand vector $\overline{\hat{D}}_i$ and the average surplus renewable power vector $\overline{\hat{S}}_j$ of each household in the past history (e.g., last week). The Eculidean distance $(d_{i,j})$ between house-

Algorithm 2 Gale-Shapley (stable marriage) algorithm.

```
Set all households to be free
while i is free and prefers to play the game with j do
    j= first household on i's list to whom i has not yet proposed
    if j is free then
        (i,j) becomes a pair
    else
        some pair (k, j) already exists
        if j prefers i to k then
            k becomes free
            (i,j) becomes a pair
        else
            (k,j) remains a pair
Return the vector of pairs which are going to play the game and cooperate during the next
week
```

hold i and household j is calculated as follows:

$$d_{i,j} = \sqrt{\sum_{h \in \mathcal{H}} |\overline{\hat{D}}_i^h - \overline{\hat{S}}_j^h|^2} \tag{5.8}$$

After that, each household defines a list of preferable households sorted in a descending order. The greater the distance between $\overline{\hat{D}}_i$ and $\overline{\hat{S}}_j$ is, the better is the matching between i and j. These lists are used as an input in Algorithm 2 to find the best matching pairs based on Gale-Shapley algorithm [231] (i.e., also known as stable marriage algorithm). The output of Algorithm 2 will be used in Algorithm 1 to run the repeated game between the selected pairs for a certain number of time periods T. In the repeated game, the selected pairs will play cooperate (C) in each stage of the game. After T time periods, each household i will calculate its discounted payoff $(r_i(s'))$ and compare it with the payoff in the case of not cooperating and purchasing the entire additional demand from the main grid $(r_i(s))$. If a cost saving is not achieved (i.e., $r_i(s) < r_i(s')$) or if it is less than a certain threshold $(r_i(s') < \varepsilon)$, household i will stop cooperating with its current pair and will enter Algorithm 2 to find another matching pair to play the game with in the following time periods. Households whose pairs defected and broke the relation will also enter Algorithm 2. The rest of households will keep playing and cooperating with the same pair in the next stage game.

Table 5.5.1: The selected groups of households and their corresponding average annual consumption.

Group	Household area (m^2)	Average annual demand (kW)	Number of households in the microgrid
Group A	81	3076	3
Group B	68.5	2384	3
Group C	47.5	2066	3
Group D	67	1714	3

Table 5.5.2: Solar PV system and performance Data.

Parameter	Value
DC System Size (kW):	1
Location:	Stockholm, Sweden
Module Type:	Standard
Array Type:	Fixed (roof mount)
Array Tilt (deg):	20
Array Azimuth (deg):	180
System Losses:	14
Invert Efficiency:	96
DC to AC Size Ratio:	1.1

5.5 Simulation Results

In this section, the simulation results are presented and the performance of the proposed distributed algorithm is evaluated. In the considered microgrid system there are $N = 12$ households that run the algorithm and play the repeated game. A time period represents one day and is divided to $H = 12$ time slots (i.e., two-hours time slots). For the ToUP, we use the electricity market spot price for Stockholm, Sweden, where data are retrieved from Nord Pool Spot [232]. Simulations are done based on real demand measurement data for residential households of different sizes and consumption patterns in a neighborhood in Stockholm, for the year of 2013. The considered groups of households are listed in Table. 5.5.1.

It is assumed that the $N = 12$ households have a solar PV system, as an onsite DER, with the same capacity, and that they generate a similar amount of renewable power with little variance (i.e., all houses are in the same area). Real hourly AC solar power measurements for one year is used,

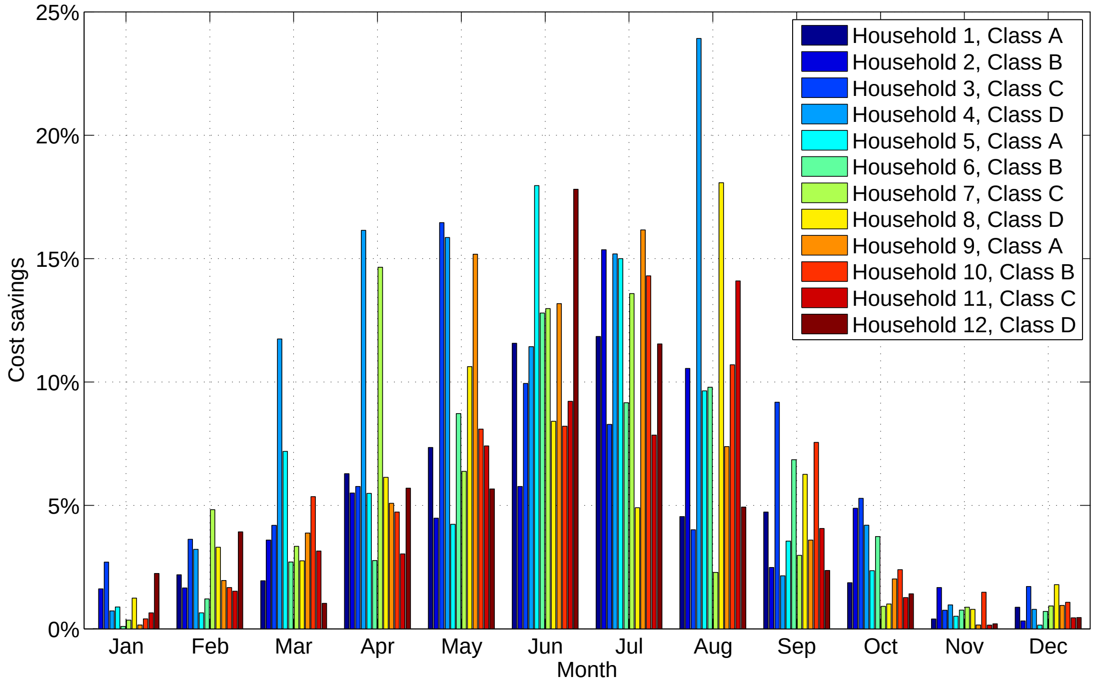


Figure 5.5.1: Average weekly cost savings of each household in every month.

which is outputted from a 1 kW solar PV system applied in Stockholm with the characteristics listed in Table. 5.5.2. Then, the renewable power of each household i at each time slot h and each time period t is selected from a normal distribution with the mean value of the solar AC power output and the standard deviation of 0.05 kW. In Stockholm, the beginning of solar panel energy harvesting, the energy peak and the end of harvesting differs a lot from season to season. Thus, the harvested energy varies in different months as well as in different days according to weather conditions.

In order to evaluate the benefit of the proposed framework, the distributed energy sharing algorithm is applied on the $N = 12$ households for one year. As mentioned in Section 5.4, Algorithm 1 is run at the end of every certain and periodic amount of time periods (e.g., one week or one month). In Fig. 5.5.1, the economical impact of the proposed distributed framework on each household participating in the energy sharing game is illustrated. It is represented by the average weekly cost saving in every month. It is assumed that all households are rational and willing to cooperate. The case in which households have an intention to cheat is out of the scope of this study.

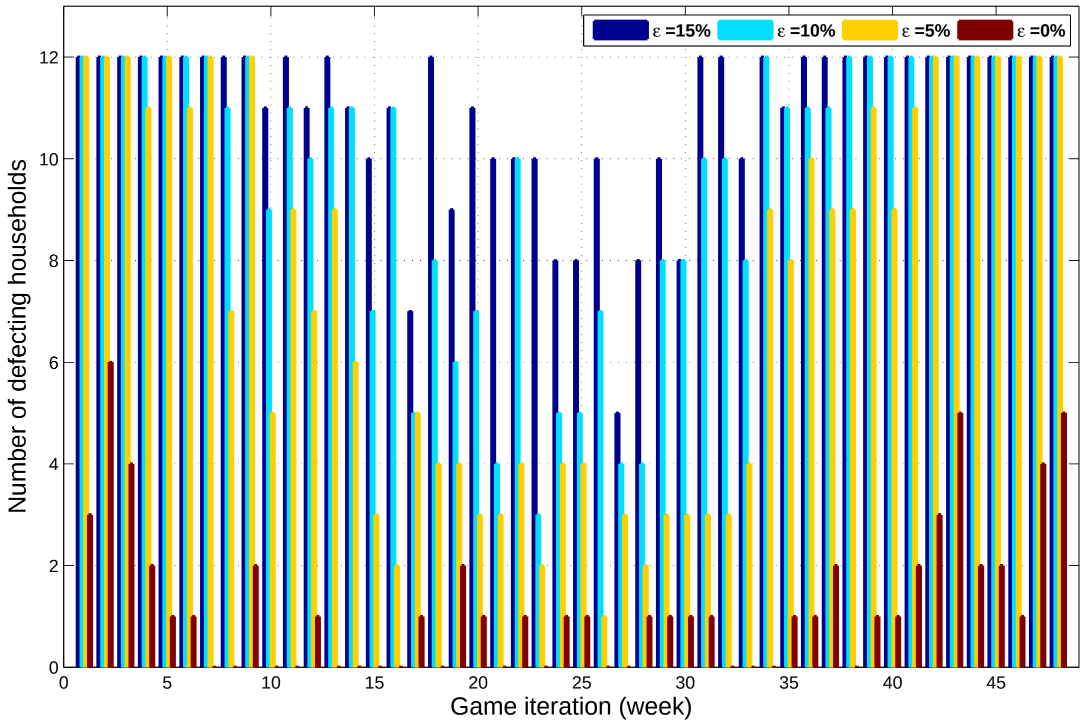


Figure 5.5.2: Temporal game evolution for different cost savings threshold.

When initializing the simulations (i.e., the first week of the year only), random pairs of households are set. After that, households are allowed, by Algorithm 1, to make a decision to continue playing the game with the same pair or to defect and look for another matching pair for the following history of time periods. In the simulation, households are allowed to do that at the end of every week. The decision is based on the achieved cost saving x_i, which is calculated as follows:

$$x_i = \frac{r_i(s) - r_i(s')}{r_i(s)} \tag{5.9}$$

where s and s' denote to the strategies of playing Defect (D) and Cooperate (C) in the recent history of time periods T (i.e., last week), respectively. In Fig. 5.5.1, households are allowed to defect if no cost saving has been achieved. A grim trigger strategy is proposed to determine the SPE, and the discount factor is set to be very close to one ($\beta = 0.95$). After that, the average weekly cost savings is calculated. As shown in Fig. 5.5.1, due to the variability in power consumption patterns of households, a household can reduce the cost of its additional demand up to 16%, in some peri-

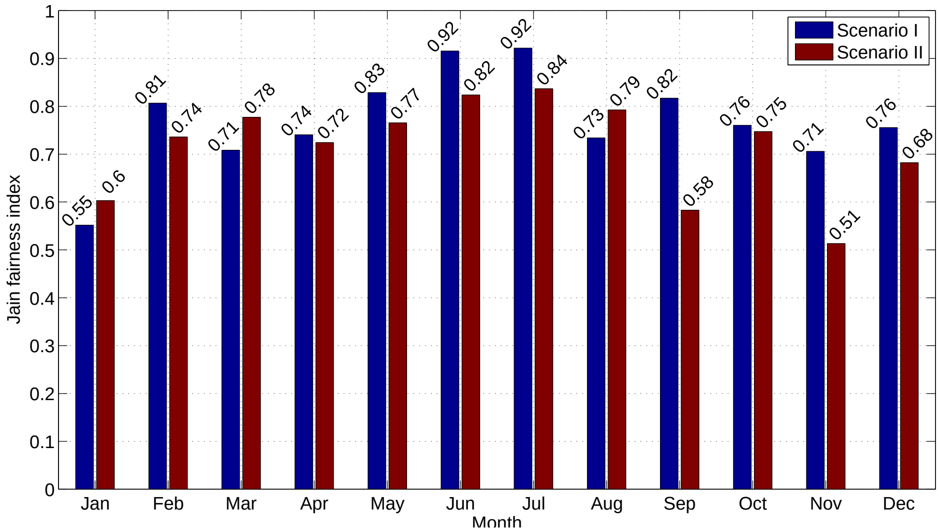


Figure 5.5.3: The fairness in cost savings achieved by all households in the two scenarios. Scenario I: households are allowed to make the decision whether to continue playing the game with the same pair at the end of every week. Scenario II: at the end of every month.

ods of the year, by exchanging some amounts of renewable energy with another household in the microgrid, instead of always purchasing the whole additional demand from the main grid. It can been noticed from Fig. 5.5.1 that the average weekly cost savings of households in every month is not strongly related to the average annual demand of each group of households presented in Table. 5.5.1. This is due to the variability and randomness in the electricity consumption behavior of households during different times of the year (i.e. from the considered real data of households' demand).

An alternative method is to allow households to defect if the cost saving x_i achieved is less than a certain threshold ε. Fig. 5.5.2 illustrates how the number of defecting households changes, as the game evolves temporally, for different cost saving thresholds ε. Every game iteration represents a history of time periods (i.e., one week) during which the repeated game between each pair of households has been daily played. It is shown that when $\varepsilon = 15\%$ the number of defecting households is relatively high. For $\varepsilon = 0$, households are allowed to defect when no cost savings has been achieved. In this case the defecting household will run Algorithm 2 and look for another matching pair to cooperate and share energy with in the following week. It can also be noticed from Fig. 5.5.2 that the number of defecting households in the four different scenarios is tightly corre-

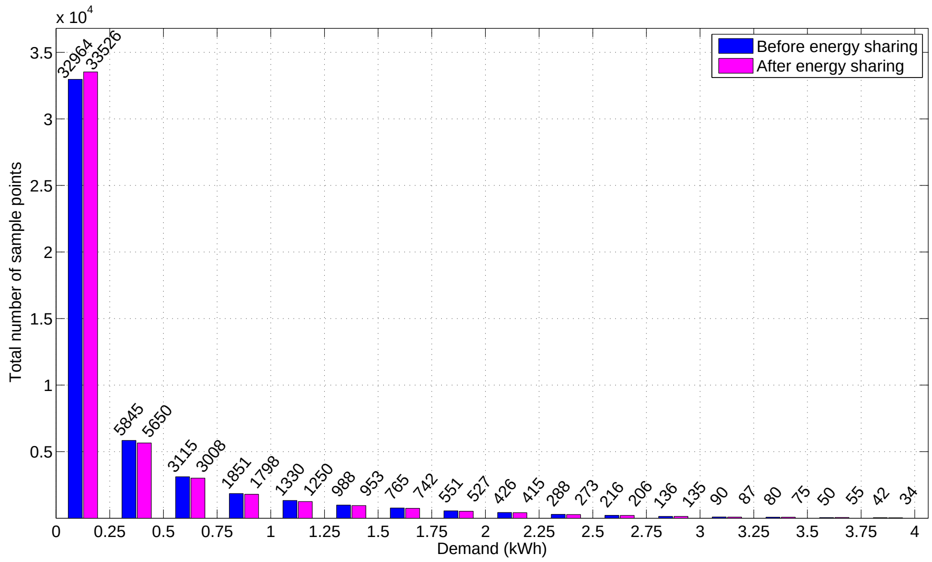


Figure 5.5.4: Histogram of the individual hourly demands of all households in one year before and after the proposed distributed energy sharing framework.

lated with the time period of the year. For instance, between April and August (i.e., iterations 15 to 32), the number of defecting households is comparatively less than other periods of the year, since the cost savings in those periods are higher. This is because the renewable energy generation profile is typically much higher in those periods in Stockholm.

In Fig. 5.5.3, the fairness in the distribution of cost savings achieved between households in every month is compared in two scenarios. In the first scenario (Scenario I), households are allowed to run Algorithm 1 and make the decision whether to continue playing the game with the same pair or not at the end of every week. In the second scenario (Scenario II), the decision to defect or not is taken at the end of every month. The Jain fairness index is used as a measurement factor. Jain fairness index is calculated as follows:

$$\mathcal{J}(x_1, x_2, \ldots, x_N) = \frac{(\sum_{i=1}^{N} x_i)^2}{N \sum_{i=1}^{N} x_i^2} \tag{5.10}$$

where $x_1, x_2, \ldots, x_N$ are the average weekly cost savings of the N household at the end of every month. It can be observed in Fig. 5.5.3 that in Scenario I if the decision, based on the discounted payoff, is made at the end of every week, the fairness in cost savings achieved by all households is

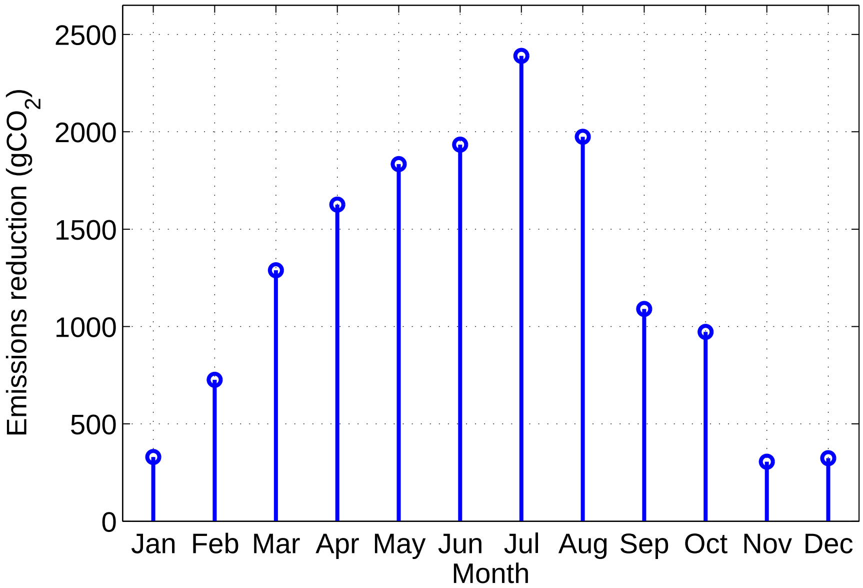


Figure 5.5.5: The CO_2 emissions per kWh of electricity demand reduced by the N=12 households in the microgrid in every month.

relatively higher in most of the months.

Fig. 5.5.4 shows the histograms of the individual hourly power demands during one year before and after applying the distributed energy sharing framework, respectively. It is shown that the individual demands that are higher than 0.25 kW are likely to be greater before adopting the energy sharing framework than after. On the other hand, the individual demands that are lower than 0.25 kW are increased after energy sharing. This is because a portion of high demands has been satisfied and/or reduced after playing the energy sharing game.

In Fig. 5.5.5, the monthly environmental impact of the proposed distributed framework is illustrated. The environmental impact is expressed as CO_2 emissions per kWh of electricity demand reduced by the N=12 households playing the energy sharing game in the microgrid. The emission factor for Sweden grid electricity is 0.02468 kgCO2 per kWh generated [233]. As shown in the figure, by using the proposed energy sharing framework, households can increase the utilization of their locally harvested renewable energy and save the emissions that would be produced if they bought their entire demand from the main grid.

5.6 Conclusions

In this study, a distributed energy sharing framework for microgrids based on a repeated game approach is proposed, where households take advantage of the variability in their power demands and consumption patterns to improve the utilization of their locally harvested renewable energy through a borrow/lend scheme.

The economical and environmental potentials of the proposed framework are assessed based on real data of demand and renewable energy generation profiles, as well as real electricity pricing data in Sweden. Simulation results show that households are able to reduce their demand costs weakly by up to 16% if they share their renewable energy and play in a cooperative manner without owning an on-site ESS. It is also shown that the proposed framework can benefit in reducing CO_2 emissions per kWh of electricity demand.

The study provides valuable insights on how a distributed energy sharing framework behaves in a microgrid with small number of households and in a place with extreme weather conditions. It opens the door to some interesting extensions and future research, including exploring and comparison with other energy sharing frameworks. It is also of our interest to investigate the economical and environmental potentials of this framework in areas located at different geographic coordinates and with different weather conditions. In addition, this work will be extended to guarantee that the matching household is able to provide a continuous supply of renewable energy for a certain request before starting the round. Finally, selfish behaviour and manipulation are also among the interesting problems related to distributed frameworks.

6

A Reputation-based Energy Sharing Framework for Microgrids with a Shared Energy Storage Unit

6.1 Motivation

In this study, we consider a microgrid scenario, where each household shares its surplus renewable energy (i.e., the remaining energy after satisfying its own demand in every time slot), by storing it in a shared battery. The surplus renewable energy is resulted from the mismatch between the local generation of renewable energy and power consumption in some time periods. The battery is controlled by an EMS that manages households' demands at different time periods, and allocates the shared renewable energy among them according to a certain policy. This framework is used in an appliances power scheduling optimization model, which jointly schedules households appliances demand and the energy that can be received from the shared battery. We focus on how to dynamically allocate the shared renewable energy among households in a way to provide fairness and efficiency to the system, by guaranteeing that all households will receive energy in proportion to their previously shared renewable energy. These issues are more meaningful in a system where households' demands may exceed the available energy in the EMS's battery at some time periods.

Since a large portion of electricity is consumed in the residential sector, involving citizens in the efficient planning and use of electricity is key. For instance, a 25% of the total electricity consumption in Spain is in the residential sector [234]. Moreover, the share of electricity used by appliances and electronics in an average household accounts for around two-thirds of its total electricity consumption, according to [234]. However, the use pattern varies depending on the different factors, such as weather conditions, household composition, family income, and cultural background, among others. Hence, the management of households' appliances power consumption can play an important role in saving costs and reducing the environmental impact of electricity consumed in the residential sector. Many demand response programs have been deployed to allow end-users to manage their power consumption in response to the prices of electricity that are changing over time, such as ToUP, CPP and RTP, among others. For example, in ToUP pricing programs, a household is expected to individually respond to time-varying electricity prices by scheduling controllable loads at times when electricity prices are cheap.

The minimum electricity cost scheduling problem of household appliances have received significant attention in the last few years [64, 235, 236]. In [235], the smart appliance power scheduling problem is modeled using MILP, capturing relevant appliance operation constraints. A distributed algorithm to schedule households' appliances aiming to minimize power costs by using game theory is presented in [64], where households are the players of the game and their strategies are the daily schedules of their appliances. In [236], an ESS is used in the appliance scheduling problem, in which the battery charges from the main grid during off-peak times, and feeds the load during peak times. While interesting, the mentioned households' appliances scheduling frameworks focus on the optimization of appliances power cost under ToUP tariff, but without considering the possibility of Distributed Generation (DG) at households. Other EMS that consider on-site small-scale ESS and Renewable Energy Source (RES) have been considered in [237–241]. However, equipping each household with an on-site ESS might be economically unaffordable due to the high cost of batteries which are required to buffer sufficient renewable energy for an average household daily power consumption [12]. Besides, batteries with long cycle life have a big physical size that makes them difficult to be located inside houses (e.g., Vanadium Redox-flow batteries [14]).

The main contributions in this chapter are summarized as follows:

- We propose a reputation-based energy sharing framework, where each household shares its surplus renewable energy by storing it in a shared battery. According to this framework, the EMS manages the available energy in the shared battery, and determines the portion of energy that will be scheduled to each household.

- We apply the proposed framework in an appliances power scheduling optimization problem which joints the scheduling of households appliances and the energy that each household can receive from the shared battery based on its reputation, taking battery's operational constraints into account.

- The performance of the proposed energy sharing framework used in appliances scheduling problem is assessed via extensive simulation experiments based on real data measurements and for different classes of households.

The chapter is structured as follows. The system model is presented in Section 6.2. The proposed reputation-based energy allocation policy is described in Section 6.3. In Section 6.4, the household appliances power scheduling is presented and the problem is formulated in Section 6.5. Numerical results are discussed in Section 6.6. Finally, we conclude the chapter and give pointers for possible future directions in Section 6.7.

The framework presented in this chapter has been firstly published in [242], and the work of appliances power scheduling problem that uses this framework has been submitted later to [243].

6.2 System Model

In this work we consider a generic microgrid which consists of a set of households $\mathcal{N}$ with a small-scale on-site RES (e.g., a solar PV system). Households are connected to the main grid and to the battery via AC power lines. They share their surplus harvested renewable energy by storing it in the shared battery that is controlled by an EMS. The EMS, in turn, controls the microgrid, manages households' demands, and allocates the shared renewable energy to them following an energy allocation policy. Households are also connected to the main grid to secure their power demands during times of the day when renewable energy generation is impossible, when there is no available energy in the battery, or when the energy available in the battery is not scheduled.

We assume that households' demands are variable both in quantity and time. At a certain time period, each household could be a supplier which shares some amount of renewable energy, or a demander which requests some amount of energy from the battery. Each household is equipped

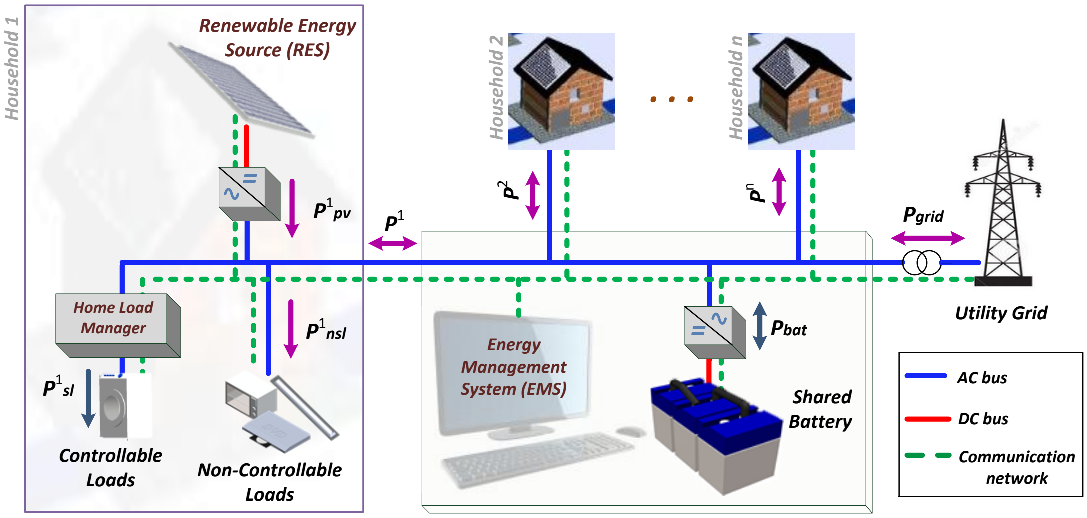


Figure 6.2.1: The proposed microgrid scheme (used in Chapter 6).

with a smart energy meter, which monitors and controls energy harvesting and power consumption intelligently. Smart meters are also responsible of data communications between households and the EMS, as well as between households and the main grid. They exchange information about households' demands, the available energy in the battery, and electricity tariffs.

The average power action of household i happens on a time slot $t \in \mathcal{T} = \{t_0, t_0 + \Delta t, t_0 + 2\Delta t, \ldots, T\}$, and denoted as $p^{t,i}$. Each time slot can represent different timing horizons (e.g., an hour). In this way, the energy is represented by the average power during a time slot of length Δt (i.e., $E = p\Delta t$). A power action of household i at time slot t could be either an interaction with main grid (i.e., injection $p^{t,i}_{\text{grid, inj}}$, or absorption $p^{t,i}_{\text{grid, abs}}$), or an interaction with the battery (i.e., charging $p^{t,i}_{\text{bat, ch}}$, or discharging $p^{t,i}_{\text{bat, dis}}$), where $p^{t,i}_{\text{grid, inj}}$, $p^{t,i}_{\text{grid, abs}}$, $p^{t,i}_{\text{bat, ch}}$ and $p^{t,i}_{\text{bat, dis}} \in \mathbb{R}$. The amount of power harvested by the local PV system of i at time slot t is $P^{t,i}_{\text{pv}}$. The proposed system architecture is illustrated in Fig. 6.2.1.

6.3 Reputation Factor

In order to model the interaction between households and the EMS, and strengthen their cooperation, we define a reputation factor R based on which the EMS will be able to dynamically allocate the available energy stored in the shared battery among households in a fair and efficient manner. A player's reputation reflects its willingness to cooperate and share its energy. Reputation-based systems belong to incentive-based mechanisms that are used in cooperation enforcement game theory [21] (see Chapter 2). They have been proposed for similar engineering problems in P2P systems [244] and grid computing [245].

The EMS keeps a reputation value for each household based on the amount of renewable energy it shares. As mentioned before, at each time slot t, household i may charge or discharge the battery with an amount of power, $p^{t,i}_{\text{bat, ch}}$ or $p^{t,i}_{\text{bat, dis}}$, respectively. The reputation of i depends on the total amount of renewable energy it shared every day d during a set of previous days D^p, with p the last day of the set. It is denoted R^p_i and calculated as follows:

$$R^p_i = \frac{\sum\limits_{d \in D^p} \sum\limits_{t \in T} p^{t,i,d}_{\text{bat, ch}}}{\sum\limits_{j \in N} \sum\limits_{d \in D^p} \sum\limits_{t \in T} p^{t,j,d}_{\text{bat, ch}}}. \tag{6.1}$$

The value of the reputation factor R^p_i represents the ratio between the total amount of renewable power shared by household i during the set of previous days D^p, and the sum of total renewable power shared by all households in the microgrid, including household i, during the same set D^p. In a similar way, the EMS calculates the reputation of other households. Reputations take positive values between 0 and 1. The higher the shared amount of renewable energy, the higher the reputation will be. This could motivate households to change their energy consumption behavior and/or share more renewable energy. A new household joins the system with a reputation equals to $1/N$, which allows it to receive some amount of energy from the EMS.

6.4 Household Appliances Power Scheduling Problem

Assume that each household i has a number of appliances A^i and wants to schedule their operation in the next 24 hours, where a time slot duration is one hour, in such a way that the cost of their total power consumption is minimized. The cost of 1 kWh from the main grid at each time slot t is assumed to be known (i.e., 24-hour ahead electricity tariff) and denoted as C^t. Each household i has shiftable and non-shiftable appliances (see Fig. 6.4.1). Non-shiftable appliances are uncontrollable and can not be scheduled. The operation of non-shiftable and some of shiftable appliances is uninterruptible, while some other shiftable appliances can be interrupted such as Plug-in Electric Vehicles (PEV) and pool pumps. Cold appliances (i.e., refrigeration) are considered as non-shiftable in terms of, for example, their low capabilities for shifting power consumption for relatively long time periods. Nevertheless, those appliances have the potential to provide short-term flexibility through small adjustments of the on/off cycles while maintaining the temperature within limits [246].

Some appliances might be used more than one time per day depending on the composition of the household and other factors. The operation happens in a time slot t and may last more than one time slot per use according to appliances' characteristics. In this study, it is assumed that there is no sequential operation constraints between appliances and that each appliance has a predetermined daily energy requirement, a maximum and a minimum power per use (i.e., taken from appliances datasheet), and a maximum execution time. The maximum allowed power for the aggregated appliances demand in each time slot is also constrained (i.e., determined by the contract with the utility company). An appliances power consumption scheduler can be deployed inside the smart meters which interacts automatically with the main grid and/or with the EMS to find the optimal appliances schedule in order to reduce the appliances demand costs. The output of the scheduler is the power profiles of the scheduled shiftable appliances and each appliance has an average power profile denoted as $p^{a,t,i}$, corresponding to the power assigned to an appliance a for household i at time slot t. The power profile $p^{a,t,i}$ takes a real value and is measured in kW (i.e., it is written in small letters, since it will be considered as a decision variable in the appliances' optimization problem in Section 6.5). $p_{\mathrm{sl}}^{t,i}$ represents the total power demand of the scheduled shiftable appliances for household i at time t. The total power of non-shiftable appliances at time t for household i is denoted $P_{\mathrm{nsl}}^{t,i}$ (i.e., it is written in capital letters, since its value will be given as an input).

6.5 Optimization Model Formulation

Using the proposed energy sharing framework in the appliances power scheduling problem can result in a significant cost saving in each household. Accordingly, the following optimization problem has been conceived as a MILP model that jointly schedules the shiftable appliances at times when electricity tariffs are cheap, and the energy that can be received from the shared battery, in order to reduce appliances demand cost.

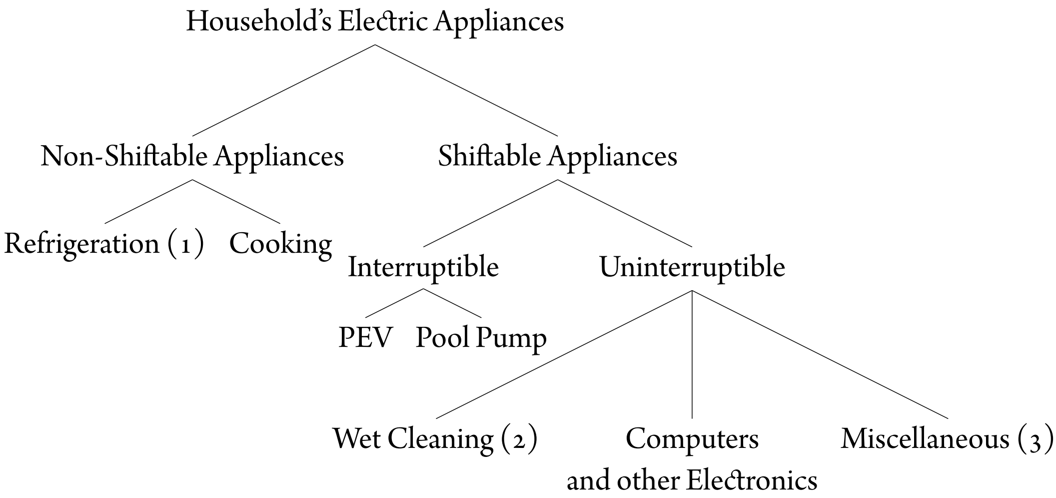


Figure 6.4.1: Classification of electric appliances in the residential sector. 1) refrigerators and freezers. 2) washing machine, clothes dryers, and dishwashers. 3) small electric devices, irons, vacuum Cleaners, kettles, among others.

6.5.1 Objective Function

The objective function aims to minimize the appliances demand costs by minimizing the amount of power absorbed from the main grid (i.e., to benefit first from the locally harvested solar energy and from the scheduled energy of the shared battery), and it is defined as:

$$\text{minimize} \sum_{t=1}^{T} C^t \sum_{i=1}^{N} R_i^p p_{\text{grid, abs}}^{t,i} \Delta t, \tag{6.2}$$

where $p_{\text{grid, abs}}^{t,i} \Delta t$ is the power absorbed from the grid, C^t is the cost of power at time slot t, and R_i^p is the reputation factor of household i. This factor is included to redistribute the shared energy stored in the battery to each household proportionally to the amount of energy it shared previously.

6.5.2 Constraints

Local Balance

The power balance between supply and demand should be assured in each household i (see Fig. 6.2.1) as follows:

$$(p^{t,i}_{\text{grid, abs}} - p^{t,i}_{\text{grid, inj}}) + P^{t,i}_{\text{pv}} + (p^{t,i}_{\text{bat, dis}} - p^{t,i}_{\text{bat, ch}}) = P^{t,i}_{\text{nsl}} + p^{t,i}_{\text{sl}}, \ \ \forall i, t, \tag{6.3}$$

Global Balance

The power exchange between households, the shared battery and the main grid can be written as:

$$\sum_{i=1}^{N} \Big((p^{t,i}_{\text{grid, inj}} - p^{t,i}_{\text{grid, abs}}) + (p^{t,i}_{\text{bat, ch}} - p^{t,i}_{\text{bat, dis}}) \Big)$$
$$= (p^{t}_{\text{grid, inj}} - p^{t}_{\text{grid, abs}}) + (p^{t}_{\text{bat, ch}} - p^{t}_{\text{bat, dis}}), \ \ \forall t, \tag{6.4}$$

where $(p^{t}_{\text{bat, ch}} - p^{t}_{\text{bat, dis}})$ represents the power available in the battery at time t.

Grid Balance

The main grid global balance is illustrated in Fig. 6.5.1(a) and formulated as follows:

$$\sum_{i=1}^{N} (p^{t,i}_{\text{grid, inj}} - p^{t,i}_{\text{grid, abs}}) = (p^{t}_{\text{grid, inj}} - p^{t}_{\text{grid, abs}}), \ \ \forall t, \tag{6.5}$$

Battery Balance

The battery global balance is illustrated in Fig. 6.5.1(b) and formulated as follows:

$$\sum_{i=1}^{N} (p^{t,i}_{\text{bat, ch}} - p^{t,i}_{\text{bat, dis}}) = (p^{t}_{\text{bat, ch}} - p^{t}_{\text{bat, dis}}), \ \ \forall t, \tag{6.6}$$

Power Boundaries

The variables related to the power absorbed from and injected to the main grid, as well as the power charges and discharges the battery, are bounded as follows:

$$0 \leq \quad p^{t,i}_{\text{grid, abs}} \quad \leq P^{i}_{\text{grid, abs}_{\max}}, \ \ \forall t, i, \tag{6.7}$$

$$0 \leq \quad p^{t,i}_{\text{grid, inj}} \quad \leq P^{i}_{\text{grid, inj}_{\max}}, \ \ \forall t, i, \tag{6.8}$$

$$0 \leq \quad p^{t,i}_{\text{bat, ch}} \quad \leq P^{i}_{\text{bat, ch}_{\max}}, \ \ \forall t, i, \tag{6.9}$$

$$0 \leq \quad p^{t,i}_{\text{bat, dis}} \quad \leq P^{i}_{\text{bat, dis}_{\max}}, \ \ \forall t, i, \tag{6.10}$$

where $P^{i}_{\text{grid, abs}_{\max}}$, $P^{i}_{\text{grid, inj}_{\max}}$, $P^{i}_{\text{bat, dis}_{\max}}$ and $P^{i}_{\text{bat, ch}_{\max}}$ are constant values defined as boundaries for each household. Particularly, the maximum amount of power household i can share with the battery, or inject into the grid are equal to the total amount of solar energy it produces at time t (i.e., $P^{i}_{\text{bat, ch}_{\max}} = P^{i}_{\text{grid, inj}_{\max}} = P^{t,i}_{\text{pv}}$). These boundaries are related to the physical AC power lines capacity and battery dynamics.

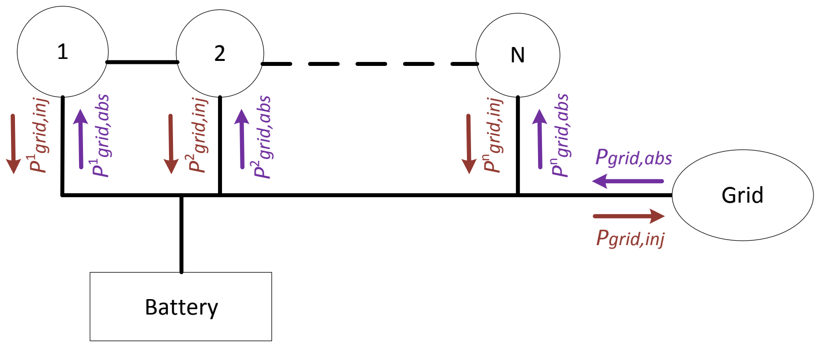
On the other hand, the power shared by each household with the battery should be safeguarded to ensure sharing only the energy produced by household's solar PV system (i.e., without charging the battery with any amount of power received from the main grid). This can be represented as follows:

$$\begin{aligned} P^{t,i}_{\text{pv}} - (P^{t,i}_{\text{nsl}} + p^{t,i}_{\text{sl}}) &\leq \mathrm{M}(1 - x^{t,i}), \ \ \forall t, i, \\ p^{t,i}_{\text{bat, ch}} + p^{t,i}_{\text{grid, inj}} - P^{t,i}_{\text{pv}} + (P^{t,i}_{\text{nsl}} + p^{t,i}_{\text{sl}}) &\leq \mathrm{M}x^{t,i}, \ \ \forall t, i, \\ p^{t,i}_{\text{bat, ch}} + p^{t,i}_{\text{grid, inj}} &\leq \mathrm{M}(1 - x^{t,i}), \ \ \forall t, i, \end{aligned} \tag{6.11}$$

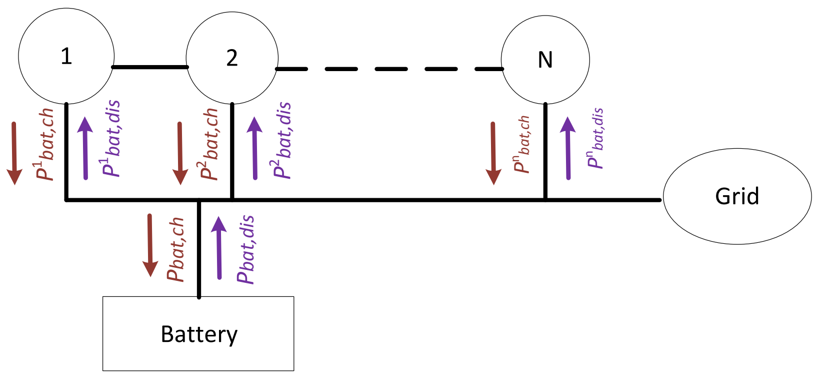
where the binary variable x^{t}_{i} is defined to determine when the generation is lower than the consumption for each household i. The value of M must be chosen sufficiently large so that the artificial variable would not be part of any feasible solution.

Energy Storage System

In an ESS, the SoC can be represented in terms of its power as the following:



(a) Battery global balance (see Eq. 6.5).



(b) Grid global balance (see Eq. 6.6).

Figure 6.5.1: Power components flow in the main bus (see Eq. 6.4).

$$\mathrm{SoC}^t = \mathrm{SoC}^{t-1} - \left(\frac{1}{\eta_{\mathrm{dis}} C_{\mathrm{bat}}} (p^t_{\mathrm{bat,\,dis}}) \Delta t - \frac{\eta_{\mathrm{ch}}}{C_{\mathrm{bat}}} (p^t_{\mathrm{bat,\,ch}}) \Delta t \right), \quad \forall t, \tag{6.12}$$

where η_{ch} and η_{dis} are the charge and discharge efficiency, respectively, and C_{bat} is the battery's capacity that depends on the technology used.

The SoC of the $k - th$ ESS is bounded as:

$$\mathrm{SoC}_{\min} \leq \mathrm{SoC}^t \leq \mathrm{SoC}_{\max}, \quad \forall t. \tag{6.13}$$

Besides, a global balance of the storage should be included to ensure equal or better conditions for the next day, as follows:

$$\sum_{t=1}^{T} \mathrm{SoC}^{t} - \mathrm{SoC}^{t-1} \geq 0, \ \ \forall t. \tag{6.14}$$

Shiftable Appliances Demand Management

Part of the demand is shiftable (P_{sl}) and can be scheduled to reduce costs.

Daily power requirement This constraint ensures that the total energy assigned to each shiftable appliance per day fulfills its daily energy consumption requirement E^{a}_{sl}.

$$\sum_{t=1}^{T} p^{a,t,i}\Delta t = E^{a}_{\mathrm{sl}}, \ \ \forall a, i. \tag{6.15}$$

Hourly demand This constraint indicates that the total power assigned to all shiftable appliances of household i at a certain time slot t is equal to its shiftable load power at that time slot.

$$\sum_{a=1}^{A} p^{a,t,i} = p^{t,i}_{\mathrm{sl}}, \ \ \forall t, i. \tag{6.16}$$

Power assignment bounds

$$P^{a}_{\mathrm{min}} y^{a,t,i} \leq p^{a,t,i}, \leq P^{a}_{\mathrm{max}} y^{a,t,i}, \ \ \forall a, t, i, \tag{6.17}$$

where P^{a}_{min} and P^{a}_{max} are the lower and upper limits of power assignment to an appliance a which are taken from appliances datasheet, and $y^{a,t}$ is an auxiliary decision binary variable that indicates whether an appliance a is switched on ($y^{a,t} = 1$) or off ($y^{a,t} = 0$) in a particular time slot t.

Peak power This constraint is to guarantee that the total shiftable power assigned in any time slot can not exceed an upper limit.

$$p^{t,i}_{\mathrm{sl}} \leq P^{t,i}_{\mathrm{peak}}, \ \ \forall a, i, \tag{6.18}$$

where $P^{t,i}_{\text{peak}}$ denotes the peak signal determined by the utility company for each time slot t and can be considered as a demand response signal.

Operation time Each household can set up a time preference constraint for each appliance. An appliance cannot be active outside its predetermined time preference interval.

$$y^{a,t,i} \leq \mathrm{TP}^{a,t,i}, \ \forall a, i, \tag{6.19}$$

where TP^a is the household's time preference for operating the shiftable appliance a (e.g., the operation time of a PEV is between 19:00 and 07:00).

Uninterruptible operation These constraints ensure a continuous operation of an appliance.

$$y^{a,t,i} \leq 1 - z^{a,t,i} \ \forall t, a, i, \tag{6.20}$$

$$y^{a,t-1,i} - y^{a,t,i} \leq z^{a,t,i} \ \forall t, a, i, \tag{6.21}$$

$$z^{a,t-1,i} \leq z^{a,t,i} \ \forall t, a, i, \tag{6.22}$$

where $y^{a,t,i}$ and $z^{a,t,i}$ are auxiliary binary decision variables used to ensure that if an appliance a starts working at a time slot t, it should not be interrupted until it finishes.

6.6 Numerical Evaluation

This section provides a performance evaluation of the proposed framework. First of all, we evaluate how the renewable energy is reallocated to each household based on its reputation. Then, we measure the economical impact on the participating households. After that, we show how the system performance is affected by the battery's capacity, the number of participating households, and the period of the year.

We consider a microgrid with $N = 3$ households that share one battery. A time period represents one day and is divided to $T = 24$ time slots (i.e., one-hour time slots). The performance of the proposed framework is measured by running the optimization model once at the beginning of the day (i.e., 24-hours ahead scheduling). We run the problem every day at the first week of every month in 2015.

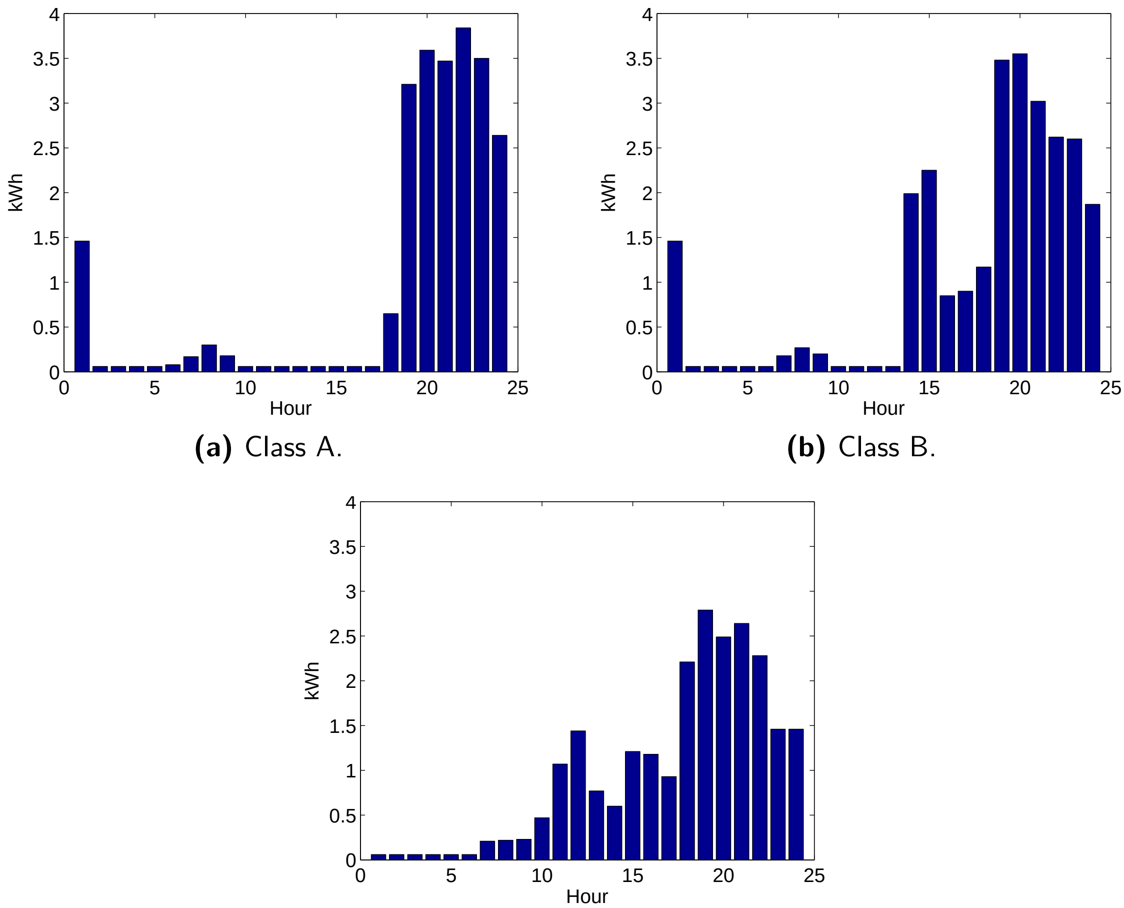
Table 6.6.1: The considered classes of households.

Class	Household's type	Occupancy pattern	Assumptions
Class A	Two adults	18:00 to 9:00 on weekdays	Full time working adults whose average daily energy consumption will be distributed throughout the day into two main periods, from 6:00 till 9:00 and from 18:00 till 01:00.
Class B	Two adults with children	13:00 to 9:00 on weekdays	One member has a full time job and the second adult holds a part time job in the morning in order to take care of the children after school.
Class C	Two pensioners	All the time	Most loads are distributed throughout the day in a random way and only what is related to cooking a specified periods.

Since the power consumption in the residential sector can vary significantly among communities (i.e., it is tightly bounded with the living habits and some social factors), we will run our simulations over households with different appliances demand profile (i.e., different classes of households) that are most common in Spain. The selected classes are listed in Table. 6.6.1.

6.6.1 Renewable Power Profile

It is assumed that the N households have a solar PV system as an on-site RES, with the same capacity, material and installation settings, and that they generate a similar amount of renewable energy with a little variance (i.e., all houses are in the same area). Real hourly AC solar power measurements are used, which are outputted from a 1.5 kW solar PV system applied in Girona, Spain, with the characteristics listed in Table. 6.6.2. The renewable power of each household i at each time slot t is selected from a normal distribution with the mean value of the solar AC power output and the standard deviation of 0.05 kW. The beginning of solar panel energy harvesting, the energy peak and the end of harvesting differs from season to season.



(a) Class A.

(b) Class B.

(c) Class C.

Figure 6.6.1: Average appliances demand profile of each considered class of households (without scheduling).

6.6.2 Appliances Demand Profile

Based on the fact that households may have different power consumption profiles, we develop an appliances demand profile generator similar to the one proposed in [247], which generates the average appliances power consumption profile for each class of households. The generator is based on a probabilistic model that predicts the possibility of each household to operate a certain amount of appliances on a certain time slot per day (e.g., there is a probability of 0.15 to run the dishwasher between 20:00-21:00, 0.3 between 21:00-22:00, 0.3 between 22:00-23:00, and 0.25 between 23:00-24:00 for households of class A). The appliances used in this tool, their power consumption, and

Table 6.6.2: Solar PV system and performance data.

Parameter	Value	Parameter	Value
DC System Size (kW):	1.5	Location:	Girona, Spain
Module Type:	Standard	Array Type:	Fixed (roof mount)
Array Tilt (deg):	20	Array Azimuth (deg):	180
System Losses:	14	Invert Efficiency:	96
DC to AC Size Ratio:	1.1		

Table 6.6.3: Household appliances and their average energy consumption: Class A.

Category	Appliance	Operation time (most likely)	No. of times per day	Average consumption per capita (kWh/day)	Average consumption per time of usage (kWh)
Cooking	Electric Oven	18:00-22:00	1	1.00	2.00
	Microwave Oven	6:00-9:00 and 18:00-22:00	2	0.23	0.23
Refrigeration	Refrigerator-Freezer	All the day	24	0.66	0.06
Electric Vehicle	PEV	18:00-01:00	7	4.90	1.40
Wet Cleaning	Washing Machine (WM)	18:00-24:00	1	0.67	1.34
	Clothes Dryer (CD)	19:00-24:00	1	1.39	2.78
	Dish Washer (DW)	20:00-24:00	1	0.625	1.25
Computers	Desktop and Laptop	19:00-24:00	5	0.40	0.16
Miscellaneous	TV	18:00-24:00	6	0.84	0.28
	Electric Kettle	06:00-09:00, 19:00-20:00 and 22:00-24:00	3	0.39	0.26
	Iron	18:00-24:00	1	0.09	0.18
	Others (e.g., Vacuum)	18:00-24:00	1	0.65	1.30

their ownership level are compiled with respect to the statistical data provided by a study that analyses the energy consumption in the residential sector in Spain [234]. This generator provides quick and easy way to generate the average appliances demand profile of any class. It uses an hourly step calculator which we believe it is enough to provide a rough estimation of the daily appliances demand. We differentiate between household's appliances demand in weekdays and weekend by adding some variability. We also add some uncertainty in household's appliances demand during

Table 6.6.4: Household appliances and their average energy consumption: Class B.

Category	Appliance	Operation time (most likely)	No. of times per day	Average consumption per capita (kWh/day)	Average consumption per time of usage (kWh)
Cooking	Electric Oven	13:00-15:00 and 17:00-21:00	2	4.00	2.00
	Microwave Oven	6:00-9:00, 13:00-15:00 and 17:00-21:00	3	0.69	0.23
Refrigeration	Refrigerator-Freezer	All the day	24	1.32	0.06
Electric Vehicle	PEV	18:00-01:00	7	9.80	1.40
Wet Cleaning	WM	13:00-24:00	1	1.34	1.34
	CD	13:00-24:00	1	2.78	2.78
	DW	13:00-24:00	1	1.25	1.25
Computers	Desktop and Laptop	13:00-16:00, 16:00-18:00, 21:00-22:00, 22:00-23:00 and 23:00-24:00	6	0.96	0.16
Miscellaneous	TV	18:00-24:00	6	1.68	0.28
	Electric Kettle	06:00-09:00 and 13:00-15:00, 16:00-18:00, 19:00-20:00 and 22:00-24:00	5	1.30	0.26
	Iron	13:00-24:00	1	0.30	0.30
	Others (Vacuum etc.)	13:00-24:00	1	1.50	1.50

weekdays. A household's appliances demand at each time slot t is selected from a normal distribution with the mean value of the appliances demand profile output, and the standard deviation of 0.1-0.15 kWh in weekdays and 0.3-0.4 in weekends.

Households' electric appliances, considered in [234], are classified into cooking, refrigeration, wet cleaning, electronics and miscellaneous. PEV is considered as a shiftable appliance as in [64, 237]. It is assumed that each appliance in the model has two states: on or off, and no appliance is left

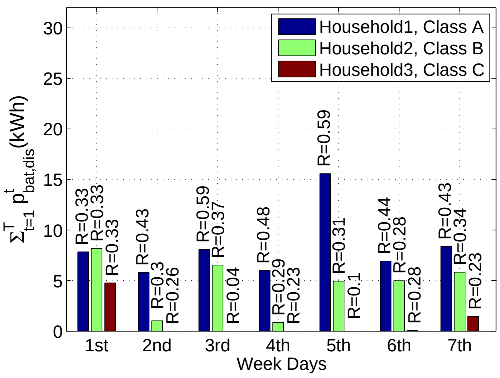
Table 6.6.5: Household appliances and their average energy consumption: Class C.

Category	Appliance	Operation time (most likely)	No. of times per day	Average consumption per capita (kWh/day)	Average consumption per time of usage (kWh)
Cooking	Electric Oven	10:00-14:00 and 17:00-20:00	1	1.00	2.00
	Microwave Oven	10:00-14:00 and 17:00-20:00	2	0.23	0.23
Refrigeration	Refrigerator-Freezer	All the day	24	0.66	0.06
Electric Vehicle	PEV	17:00-00:00	7	4.90	1.40
Wet Cleaning	WM	12:00-21:00	1	0.67	1.34
	CD	13:00-21:00	1	1.39	2.78
	DW	18:00-21:00	1	0.625	1.25
Computers	Desktop and Laptop	14:00-16:00 and 17:00-22:00	2	0.30	0.30
Miscellaneous	TV	9:00-10:00 and 10:00-11:00, 14:00-15:00, 16:00-17:00, 18:00-19:00, 20:00-21:00 and 21:00-22:00	8	1.12	0.28
	Electric Kettle	06:00-09:00 and 11:00-14:00, 14:00-18:00 and 20:00-22:00	4	0.52	0.26
	Iron	09:00-21:00	1	0.09	0.18
	Others (Vacuum etc.)	09:00-21:00	1	0.37	0.74

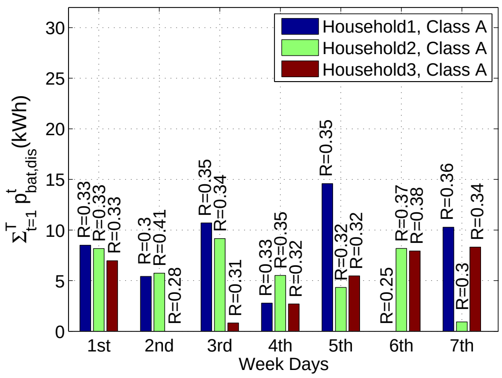
on standby. Many appliances, such as a refrigerator-freezer, are assumed to have a constant power demand when switched-on. Other appliances could be represented by time-varying demands. For example, a washing machine that runs through various stages of water heating, washing and spinning, significantly varies its demand throughout a cycle. However, such detailed appliance demand cycle data is not generally available. Thus, and for the sake of simplicity, we calculate appliances' required demand per each time slot based on their total daily demand and operation periods (e.g., if the washing machine is used one time per day, where it requires 1.34 kWh and lasts two hours on average to complete its operation, then its demand per each time slot is 0.67 kWh). The selected

Table 6.6.6: The values of the problem parameters used in simulations.

Parameter	Value	Parameter	Value
$P^{i}_{\text{grid, abs}_{\text{max}}}$ (kW)	6	$P^{i}_{\text{bat, dis}_{\text{max}}}$ (kW)	2
SoC_{min} (%)	20	SoC_{max} (%)	100
SoC_{0} (%)	60	C_{bat} (kWh)	[5, 30]
η_{dis}	[0, 1]	η_{ch}	[0, 1]
$TP^{a,t,i}$	PEV: 19:00-07:00. DW, WM and CD: 06:00-23:00	$P^{t,i}_{\text{peak}}$ (KW)	3.6
$P^{a}_{\text{min}} = P^{a}_{\text{max}}$ (kW)	PEV: 1.4, DW: 0.625, WM: 0.67, CD: 1.39		



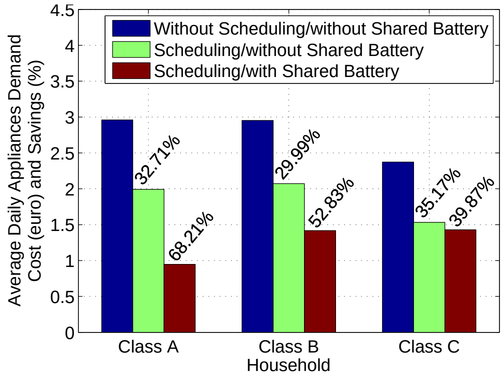
(a) Households of different classes.



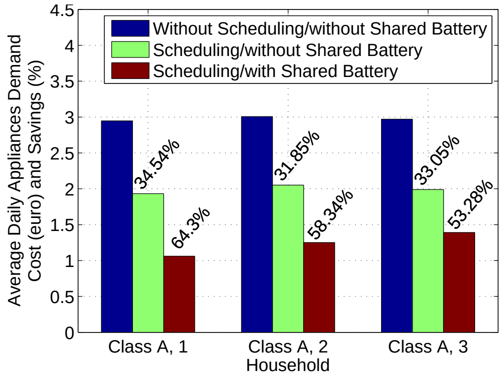
(b) All Households are of class A.

Figure 6.6.2: Daily amount of power received from the battery based on households reputation in the first week of July 2015.

household appliances and their daily average power consumption for each class of households are presented Table. 6.6.3, Table. 6.6.4 and Table. 6.6.5. The listed operation times are the operation times in the ordinary case (i.e., without scheduling). It is assumed that all households in the considered microgrid have one of the listed appliances. In this numerical evaluation, each household has four shiftable smart appliances including a DW, a WM, a CD and a PEV. The average appliances demand profiles of the selected classes of households of all week days are shown in Fig. 6.6.1.



(a) Households of different classes.



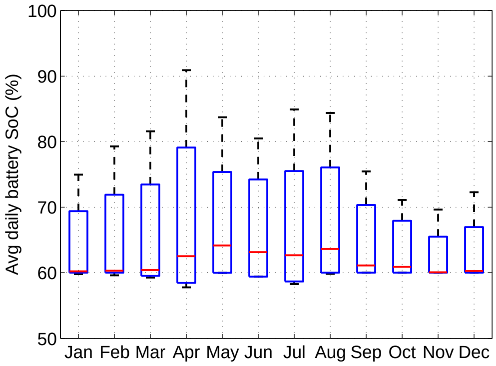
(b) All Households are of class A.

Figure 6.6.3: Households average daily cost savings in the first week of July 2015.

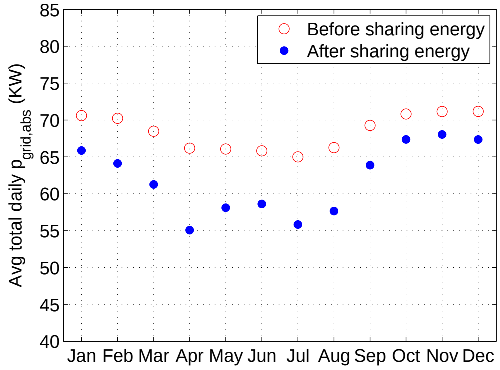
6.6.3 Simulation Results

This section presents the simulation results of the optimization problem presented in Section 6.5. The MILP problem is coded in GAMS 24.2.3 [248] and solved using IBM ILOG CPLEX Optimization Studio [249]. MATLAB R2014a is used as an interface. For the electricity pricing tariff, we use the ToUP rate of the market in Spain in 2015 [250]. The execution period is from 00:00 till 24:00, and the length of time slots is 1 hour. The value of each parameter used in this simulation is provided in Table. 6.6.6. Unless it is mentioned otherwise, we assume that the microgrid uses a battery of a 30 kWh capacity with an initial SoC equal to 60%, and an efficiency of charge and discharge equal to 1.

In Fig. 6.6.2, the daily allocation of power by the shared battery ($p_{\text{bat, dis}}$) for each household in the first week of July 2015 is presented. The figure shows the allocation for households of different classes, and of the same class (i.e., class A), in Fig. 6.6.2(a) and Fig. 6.6.2(b), respectively. The reputation is updated every day (i.e., $D^p = \{1\}$), and the total allocation is calculated at the end of the day. When households join the system, they start with an equal reputation. We set the initial reputation to $R = 1/N$. It is observed from Fig. 6.6.2 that the allocation of renewable energy strongly depends on households' reputation even if the differences between their reputations are small. It is worth to highlight the correlation between the reputations, and the amount and distribution of appliances demand during the day (see Fig. 6.6.1). For instance, the appliances demand of households belonging to class C has a higher match with their solar PV energy gener-



(a) Average min and max SoC reached.



(b) Average amount of the total received power from the grid.

Figure 6.6.4: System performance during every month in 2015, (three households of class A, B and C).

ation profile than other classes of households. Therefore, their shared surplus renewable energy is less than other classes, which makes their reputation lower and the resulted allocation of power in future time periods less. The MILP solver starts allocating the energy available in the battery to the household with the highest reputation, then it moves to next households in a descending order based on reputation. However, it may happen that the battery will not have enough available energy when the solver reaches households with low reputations. It can be noticed from Fig. 6.6.2(a) that the amount of power allocated to households of class A is always higher than to other classes, since their reputation is higher. This is because the amount of surplus renewable energy shared by households of class A is higher than other classes due to their occupancy pattern (i.e., from 18:00 to 9:00, see Table. 6.6.1).

It can also be observed that the households not always receive renewable energy from the battery, such as the class C household, although they share some amount of renewable energy every day. However, we argue that this type of households still have incentives to keep their cooperation, since they may share more energy some days and get higher reputation in the next day. For instance, assume a household of class C (i.e., with a typically low reputation) goes out for one day, its reputation when it comes back will be much higher than the others, and it will receive more power from the battery.

In order to evaluate the economical impact of the proposed framework, we calculate and com-

Table 6.6.7: The effect of the number of households on the min and max SoC and the total absorbed power from the main grid.

Capacity (kWh)	Parameter	Number of households (N)			
		3	4	5	6
C_{bat}=30	$\sum p_{\text{grid, abs}}$ (kW)	56.97	74.26	95.29	112.27
	$\text{SoC}_{\text{max}}^{\text{reached}}$ (%)	83.66	94.02	95.57	94.83
	$\text{SoC}_{\text{min}}^{\text{reached}}$(%)	59.23	59.01	58.42	56.75
C_{bat}=15	$\sum p_{\text{grid, abs}}$ (kW)	56.69	73.77	94.83	111.77
	$\text{SoC}_{\text{max}}^{\text{reached}}$(%)	94.89	99.83	99.95	99.37
	$\text{SoC}_{\text{min}}^{\text{reached}}$(%)	58.07	51.31	46.34	46.58
C_{bat}=7.5	$\sum p_{\text{grid, abs}}$ (kW)	56.36	73.36	94.28	111.25
	$\text{SoC}_{\text{max}}^{\text{reached}}$(%)	97.29	99.76	100.00	98.75
	$\text{SoC}_{\text{min}}^{\text{reached}}$(%)	54.29	39.36	41.56	38.30

pare the appliances demand costs in three different scenarios. In the first scenario, the daily appliances demand cost is calculated in the ordinary case (i.e., without scheduling the shiftable appliances and without using the shared battery). In the second scenario, the shiftable appliances are scheduled at times when electricity tariffs are cheap, but without using the shared battery. In the third scenario, the proposed framework is used, where a household is allowed to schedule the shiftable appliances and use the shared battery. In all scenarios households are assumed to share only their surplus renewable energy.

In Fig. 6.6.3, the economical impact of the proposed framework on each participating household, represented by the average daily appliances demand cost and the average daily cost saving, is presented. We run the three different scenarios in the first week of July 2015. These scenarios are compared in two situations: i) when the households are of different classes, in Fig. 6.6.3(a), and ii) when all households are of the same class (i.e., class A), in Fig. 6.6.3(b). It is assumed that no additional payments are made to any household for the power received from the shared battery. The figure shows that after applying the proposed appliances scheduling framework using the shared battery (i.e., third scenario, red bars), the daily cost of appliances demand is reduced up to 68%, which is close to twice the saving obtained in the second scenario (i.e., green bars, up to 35%). This means that using the proposed framework, households can achieve a higher cost savings by only sharing their surplus renewable energy. We note that the savings in the red bars are the savings with respect to the original cost (blue bar).

Fig. 6.6.4 shows how the performance of the system tightly depends on the period of the year and external weather conditions. In this simulation experiment, we consider a microgrid scenario that consists of three households of different classes. Fig. 6.6.4(a) illustrates how the the average minimum and maximum SoC reached (i.e., $\mathrm{SoC}_{\mathrm{min}}^{\mathrm{reached}}$ and $\mathrm{SoC}_{\mathrm{man}}^{\mathrm{reached}}$, respectively) varies every month according to the amount of solar energy generated in Girona in 2015. Fig. 6.6.4(b) shows how sharing the surplus renewable energy by households has a positive effect in reducing the total demand absorbed by the microgrid as a whole ($\sum\limits_{t\in\mathcal{T},i\in\mathcal{N}} p_{\mathrm{grid,\,abs}}^{t,i}$, see Fig. 6.5.1(a)).

From Fig. 6.6.4(a), we notice that the nominal minimum SoC has not been reached in this scenario (i.e., $\mathrm{SoC}_{\mathrm{min}}$=20% in our simulation settings). This is because the EMS needs to guarantee a certain initial SoC at the beginning of next day (i.e., SoC_0= 60% in our simulations, see Eq. 6.14). In order to do that, the optimizer does not allow the battery SoC to go below a certain value, depending on the battery capacity, the amount of shared solar energy, and the number and class of participating households.

Therefore, we further study the effect of the battery capacity C_{bat} and the number of participating households N on $\mathrm{SoC}_{\mathrm{min}}^{\mathrm{reached}}$, $\mathrm{SoC}_{\mathrm{man}}^{\mathrm{reached}}$, and $\sum\limits_{t\in\mathcal{T},i\in\mathcal{N}} p_{\mathrm{grid,\,abs}}^{t,i}$, by running the experiments presented in Table. 6.6.7. We assume that households are of different classes (i.e., Household 1, 4 are of class A, 2, 5 are of class B, and 3, 6 are of class C) and all of them have the four shiftable appliances mentioned before. In this experiment, we have the same previous simulation settings except η_{dis}= 0.9 and η_{ch}=0.95. Table. 6.6.7 shows how the system allows the battery to reach a lower $\mathrm{SoC}_{\mathrm{min}}^{\mathrm{reached}}$ if its size is smaller or when the number of households in the microgrid increases. The first case is due to the limited size of the battery. In this case, the system allows a lower $\mathrm{SoC}_{\mathrm{min}}^{\mathrm{reached}}$, and at the same time it guarantees the required initial SoC_0 at the beginning of the next day. The second case is because of the increased amount of shared renewable energy. It is clear to notice from Table. 6.6.7 that the microgrid absorbs more power from the main grid as the number of households increases (i.e., more households means more demand).

6.6.4 Scalability and Computation Time

In order to show the applicability of the proposed framework in real scenarios, the solving time of the scheduling optimization problem is computed for different number of households in the microgrid. The problem is run one time per day (i.e., 24-hours ahead scheduling). It is coded in GAMS 24.2.3 and solved using CPLEX 12 in a modern laptop (i.e., i7 at 2.4 GHz, 4 GB of RAM, 64-bit Windows). We assume that the ownership of shiftable appliances may differ from household to

Table 6.6.8: Computation time in seconds.

Number of households (N)	Number of shiftable appliances (A)			
	1	2	3	4
3	1.938	2.390	4.155	6.71y
5	2.073	2.649	6.555	14.086
7	2.255	3.546	9.901	19.565
10	2.548	4.154	11.865	24.385

household, thus, the computation time for different number of shiftable appliances in each household is further calculated in each case. Table. 6.6.8 shows the statistics of the computation time for solving the appliances scheduling cost minimization problem in each case. It can be noticed that the number of households and the ownership of shiftable appliances have a significant impact on the computation time. However, the computation time is reasonable even for large number of households connected to a single battery.

6.7 Conclusions

In this chapter, a reputation-based cooperative energy sharing framework for microgrids is used in a dynamic appliances power scheduling cost minimization problem. In this framework, households aim to maximize the utilization of their on-site renewable energy source by storing their surplus renewable energy in a shared battery. In this problem, households appliances are not only scheduled at times when electricity tariffs are cheap, but are also allowed to use the scheduled energy of the shared battery.

Simulation results assess the performance of this framework and show how households are able to achieve a monthly cost saving of up to 68% by sharing only their surplus renewable energy. It is shown that their cost saving is tightly related with their reputation, that increases as they share more renewable energy. Further simulation experiments have been conducted to show the effect of the battery capacity and the number of participating households on the maximum and minimum battery's state of charge reached, and on the total amount of power absorbed from the main grid. In addition, we show that the problem solution can be obtained in a reasonable computation time for different number of households and different ownership level of shiftable appliances.

This study provides valuable insights on how a microgrid community with a shared battery can reduce power demand and increase cost savings in different periods of the year without urging households to have a local ESS. Future work will focus on applying this framework in real time which imposes additional supervisory control and prediction models.

7

Conclusions and Future Works

7.1 Conclusions

Smart grids has been conceived as the future power systems, providing fundamental economic and environmental benefits. It is clear that considerable efforts are needed to ease this transition by resolving numerous economic, commercial, and technical challenge. The emergence of smart grids may ultimately radically change the way our ever expanding electricity demand is met, especially in places poorly served by the traditional power system.

In this dissertation, problems related to two different components of the smart grid infrastructure, namely the smart communication system, and the smart energy system, have been investigated. With respect to the smart communication system, a survey that explores the use of game theory for addressing the energy efficiency and lifetime maximization problems in different domains of WSNs is presented in Chapter 3. A novel taxonomy of games applied in WSNs is given. Each domain starts with an introduction which presents and discusses the recent work done for addressing energy efficiency problems in that domain using non-game theory approaches. Then, we present the different game theory proposals. At the end of each domain, a separate section for discussion and future directions is specified, which places special emphasis on: i) lessons learned in each domain, ii) what is the most appropriate game class for that domain, iii) strength and pitfalls of proposals, and iv) a guidance about some gaps that need to be addressed in future work. The survey is supported by comparative tables and statistical charts that overview how this research area has evolved in the last few years, and summarize the work achieved in each domain in a graphical manner. The work shows that game theory models have intensively been used for addressing the energy efficiency problem in WSNs.

In Chapter 4, we analyze the energy consumption of some recent and baseline MAC protocols in low data rate delay-tolerant WMSNs and their applications in smart grids. To achieve that, a multi-class traffic model is derived and used to model the energy consumption of MAC protocols from different categories, including asynchronous (sender-initiated and receiver-initiated), and synchronous (locally and globally) MAC protocols. Using those models, the performance of the MAC protocols is compared as a function of the network topology, the density of MMSs, and the sampling rates. The study shows that asynchronous MAC protocols outperform synchronous ones. In particular, it demonstrates that receiver-initiated MAC protocols achieve a better performance than sender-initiated ones. Predictive-Wakeup MAC protocol (PW-MAC) is recommended as the best candidate for this kind of networks in terms of low energy consumption and wide range of sampling rate for a comparatively flexible network topology parameters and densities of MMSs. The study reveals that some MAC protocols designed originally for scalar WSNs could be suitable for low data rate delay-tolerant WMSNs and its applications.

In addition to energy efficiency, it is important to note that remote and timely information gathering about equipment failures, capacity limitations, and natural accidents is extremely needed for ensuring proactive, real-time, reliable and efficient diagnosis of possible failures in the smart grid, where the analytical tools of game theory can play an important role.

Regarding the smart energy system, two different energy sharing frameworks are proposed for smart grids and microgrids based on a game theory approach, where households take advantage of the variability in their power demand to improve the utilization of their locally produced renewable energy. In the first framework, presented in Chapter 5, it is shown that households can reduce their demands from the main grid by exchange some amount of renewable energy among each other in a peer to peer fashion. Households' interaction is modeled as a repeated energy sharing game. The economical and environmental potentials of this framework are assessed based on real demand and renewable energy generation profiles, as well as real electricity pricing data in Sweden. Simulation results show that households are able to reduce their demand costs by up to 16% if they share their renewable energy and play in a cooperative manner without owning an on-site ESS. The framework is totally distributed. However, it is found that a considerable amount of renewable energy is remained in some households after energy sharing, due to the fairness metrics imposed by the matching algorithm.

In order to maximize the utilization of the surplus renewable energy, a second energy sharing framework is presented in Chapter 6. In this framework, households share all their surplus renewable energy by storing it in a shared battery that is controlled by an EMS. The EMS manages the battery and reallocates the shared available renewable energy according to a reputation-based energy allocation policy, where each household receive and amount of energy in proportion to its reputation, represented by the amount of energy shared previously. This framework is used in an autonomous appliances power scheduling optimization problem, in which households do not only schedule the operation of their appliances at times when electricity tariffs are cheap, but are also allowed to use the available energy scheduled by the EMS, taking battery's operational constraints into consideration. The economical potential of the proposed framework is assessed in multiple scenarios and compared with the classical appliances scheduling problem. Numerical analysis is conducted using real data of renewable energy and appliances demand profiles, as well as real electricity pricing data, for different classes of households and different annual periods in Spain. Results show that the proposed reputation-based policy guarantees fairness in energy allocation, and that households are able to achieve a better utilization of their renewable energy, reducing their appliances demand costs by up to 68%.

These studies provide valuable insights on the performance of energy sharing frameworks using game theory in microgrids. It is noticeable that game theory formulations and models are very suitable for addressing various problems in smart grids and can be helpful in increasing their efficiency and reliability. To conclude, we believe that this dissertation fills a need in the area of smart grids and we hope it will be helpful for any researcher who wants to start contributing or further exploring this promising research domain.

7.2 Future Works

Future work should focus on different aspects related to energy sharing frameworks. Regarding the first proposed framework, we aim at improving the utilization of the remained surplus renewable energy, either by exploring different matching algorithms, or by proposing a multiple-households energy sharing game instead of the two-households game proposed in this work. In addition, this work should be extended to guarantee that the matching household is able to provide a continuous supply of renewable energy for a certain request before starting the round of the game. Regarding the second framework, further enhancement of the optimization problem could be achieved by considering system-wide losses. Besides, future work should focus on applying this framework in real time which imposes additional supervisory control and prediction models. Energy sharing between multiple neighboring microgrids when, for instance, working in islanded mode is an interesting problem to tackle in this area. Furthermore, selfish behavior and manipulation are also among the important problems that need to be considered in energy sharing frameworks. Finally, additional efforts in laboratories and in pilot installations are strongly needed to demonstrate the benefit of energy sharing frameworks and game theory in smart grids.

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