

Game Theoretic Load Management Schemes for Smart Grids

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Abstract

To achieve a high level of reliability, efficiency, and robustness in electric systems, the concept of smart grid has been proposed. It is an update of the traditional electric grid designed to meet current and future customers' requirements. With the smart grid, demand management has been adopted in order to shape the load pattern of the consumers, maintain supply-demand balance, and reduce the total energy cost. In this thesis, we focus mainly on energy savings by critically investigating the problem of load management in the smart grid. We first propose a user aware demand management approach that manages residential loads while taking into consideration users' comfort. This latter is modeled in a simple yet effective way that considers waiting time, type of appliance, as well as a weight factor to prioritize comfort or savings. The proposed approach is based on game theory using a modified regret matching procedure. It provides users with high incentives to participate actively in load management and borrows advantages of both centralized and decentralized schemes. Then, we investigate the issue of fairness within demand response programs. The fair division of the system bill stemming from the use of shared microgrid resources with different costs is examined. The Shapley value provides one of the core solutions to fairness problems; however, it has been known to be computationally expensive for systems such as microgrids. Therefore, we incorporate an approximation of the Shapley value into a demand response algorithm to propose a fair billing mechanism based on the contribution of each user towards attaining the aggregated system cost. Finally, we study energy trading in the smart grid as an alternative way to reduce the load on the grid by efficiently using renewable energy resources. We propose a solution that takes into account the smart grid physical infrastructure, in addition to the distribution of its users. Different constraints stemming from the nature of the smart grid have been considered towards a realistic solution. We show through simulation results that all of the proposed schemes reduce the load on the grid, the energy bills, and the total system energy cost while maintaining the users' comfort as well as fairness.

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Dedication

To My Parents who have supported me throughout every step of this work. To my husband Imad, and last but not least, to my dear brothers Reda, Tarek, and Yassine. This is dedicated to the ones I love.

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List of Symbols

Symbol	Description
AMI	Automatic Metering Infrastructure
AMR	Automatic Meter Reading
CI	Confidence Interval
CL	Confidence Limits
CPP	Critical Peak Pricing
DA	Distribution Automation
DER	Distributed Energy Resources
EMCs	Energy Management Controllers
ESS	Energy Storage System
EVs	Electric Vehicles
Fi-Wi	Fiber-Wireless
HAN	Home Area Network
HEM	Home Energy Management
HMS	Home Energy Management System
IBR	Inclining Block Rate
ICT	Information and Communication Technologies
KKT	Karush Kuhn Tucker
NAN	Neighborhood Area Network
MINLP	Mixed Integer Nonlinear Programming
NIST	National Institute of Standards and Technology
OMS	Outage Management System

PHEVs	Plug-in Hybrid Electric Vehicles
PLC	Power line Communications
PV	PhotoVoltaic
QoS	Quality of Service
RTP	Real Time Pricing
SAS	Substation Automation System
SEP	Smart Energy Profile
TCP	Transmission Control Protocol
TOU	Time-Of-Use
V2G	Vehicle to Grid
V2H	Vehicle-to-Home
WAN	Wide Area Network
WAS	Wide Area Situational Awareness
WMN	Wireless Mesh Network

Chapter 1

Introduction

1.1 An Overview of the Smart Grid

Recently, climate change, increased energy dependency on fossil fuels as well as scarcity in such natural resources have resulted in a global evolution on how energy is generated and consumed. Utility companies were forced to rethink their electricity generation and delivery from the bottom up in order to face unprecedented challenges. These include strict regulations, concerns about the environment, and growing customer expectations. Lack of information about customers and the state of the electric grid in addition to the aging infrastructure add complexity to the operation of utility companies. The energy demands are expected to increase significantly in the next decade. According to [1], consumption will have increased by 75% by the year 2020 compared to 2000. This rise will come from the introduction of different chip technologies and automated manufacturing such as industrial automation and consumer electronics. This exponential increase puts tremendous stress on existing electrical grids which are becoming larger, interconnected, and vulnerable. The traditional grid was not initially built to transfer huge amounts of electricity under heavy consumers' demands. This resulted in a sequence of immense blackouts affecting millions of people all over the world. For instance, as stated in [1], there were 13 blackouts in 2005, 19 in 2006, 13 in 2007, 21 in 2008 and 14 in 2009. This could affect a huge number of people as in 2012 where 620 million people were affected by a major blackout in India. Traditionally,

the electric grid is characterized by having a broadcast nature where all the necessary electricity for a region is generated at some central powers stations; then, using a vast network of cables and transformers, the electricity is distributed to consumers. In order to guarantee that the countless electricity demands are satisfied, various load forecasting models were developed over time. Data gathered from forecasting models is not always accurate and usually pushes utility companies to generate higher energy amounts in order to ensure there is enough energy supplied to its customers. This results in a waste of resources and energy.

Unfortunately, the electric system did not take advantage of the innovation and technology that has dramatically enhanced other industrial sectors. The electric grid has been passive for decades and operated in the same way. Recently, utility companies and governments have realized the need to upgrade the traditional electric grid in order to face its inefficiency and unstable state. Concerns about the environment have caught the attention of many governments and organizations which are encouraging utility companies to reduce the effects caused by greenhouse gas by enabling low-carbon energy technologies. In Europe, these changes are reflected in the 20-20-20 targets: 20% carbon reduction, 20% rise in energy efficiency and 20% production from renewable resources by the year 2020 [2].

In order to solve the limitations of the traditional electric grid, namely enhance the efficiency of energy, reduce energy consumption, introduce clean Distributed Energy Resources (DERs), and diminish the effects on climate change; the traditional electric grid must undergo major modifications. The smart grid is a new concept that has been recently proposed to update the electric grid to make it able to meet the current and future customers' requirements.

The Smart Grid is an electrical system that it is able to take intelligent decisions in different parts of the electric infrastructure to keep a stable operating environment. There is no clear and concise definition of the smart grid but it can be easily defined based on its features and functions. It is an upgrade of the traditional grid having the same basic functions with different enhancements. More details on smart grid are illustrated in Appendix A. The added intelligent smart grid functionalities can be summarized as

follows [3]:

- Self-healing: The smart grid is a self-healing system, where the energy flow is monitored and evaluated in an autonomous manner. This self-assessment guarantees a continuous flow of energy even if in the case of system disturbance such as interruption of transmission cable. As result, less power outages will occur, which increases the system reliability and consumer's satisfaction.
- Resilient to attacks: Smart grid is supposed to have a strong safety mechanism from both physical attacks such as natural disasters and cyber-attacks. The electrical grid is considered as critical asset in many countries as all the other economic sectors rely on the electricity to be working. Therefore, any type of attacks could affect not only the society's welfare but also the country's economic growth.
- Increases energy quality: besides offering the availability and delivery of energy, smart grid is expected to increase the quality of the delivered energy by reducing the amount of voltage fluctuations. For instance, in some manufacturing process, a variation in the voltage such as a dip that goes on for less than 100 milliseconds could result in similar effect to power outage for several minutes. According to [3], unsteady power flow can cost up to millions of dollars per event in the commercial facilities.
- Optimizes assets and operates efficiently: asset management is enabled based on continuously and automatically monitoring the different components of the smart grid. Less equipment will be prone to failure as their degradation can be tracked. The smart grid will also integrate various new technologies that are able to decrease the amount of energy loss in the whole power system from generation to delivery. Hence, both the reliability and the efficiency of the electric grid is improved and enhanced.
- Consumers' motivation and involvement: Thanks to the two-way flow of power and information, the smart grid provides the consumers with various type of information. This will help the consumers in many ways; taking better energy management actions

and saving money. It will also motivate power suppliers to compete and offer better services.

- Incorporation of all generation options: the smart grid will support both the traditional non sustainable fossil fuels energy sources as well as new alternative sources. Most of these resources will be installed over disperse areas as opposed to the traditional way where the generation is performed in one central location. These new renewable energy sources will make distributed power generation available in the electrical system. Various complications could be raised by the integration of these resources such as irregular power supply due to the unavailability reasons.
- Enables energy markets: The competition between service providers will be promoted thanks to the energy markets in the smart grid. This is very beneficial for the consumer since more choices will be available and lower prices will be offered by the suppliers. Moreover, the use of many distributed resources across residential and industrial areas will bring new power suppliers into energy markets and more efficient means of power generation. Energy markets will manage the buyers and sellers of power which results into different prices depending on the supply and the demand.

1.2 Motivation

One of the most important applications of the smart grid that has gained much attention from both academia and the industry is load management. This is due to the challenges facing the electric grid mentioned above. Particularly, the tremendous stress coming from increased residential energy demands with the emergence of the electrical vehicles, increase in the fuel cost, and scarcity of natural sources. In fact, multiple works have addressed this issue in the literature by developing demand response programs.

Demand response can be described as the set of mechanisms used by the utility companies to manage end-user energy consumption in response to supply conditions. Improving electric grid reliability, lowering the use of electricity during peak demand, increasing energy efficiency, providing a cheaper operation of the whole power systems, and matching

the demands to the available supply are all goals of demand response programs. However, in order to achieve these goals, demand management mechanisms must incorporate a set of features that push both the utility companies and consumers to adopt it. These often come in the form of savings in costs for the utility, and in the energy bill for users.

Unfortunately, based on the available literature, users' comfort is often left out of the demand response equation leading to unsatisfied users. This poses a challenge for the implementation of demand response programs in real life. Therefore, there is a need for sophisticated demand response algorithms that will efficiently achieve the previously mentioned goals while taking into consideration consumers satisfaction.

As the number of users participating in demand response grows larger, the effect of demand management increases since it will be likely to have more adjustable loads when demand changes. Thus, it is crucial to solve large-scale demand response problems in an efficient manner. This favors the use of distributed and decentralized approaches to solve scalability issues.

Participating in demand response creates privacy concerns for its users. The type of information shared as well as the entities with whom it is shared are two important issues that need to be considered while developing demand response programs. Although the monetary incentives provided by demand response might be quite interesting to some users, others may refrain from participating due to privacy concerns. Consequently, a demand management mechanism should incorporate the previously mentioned aspects in order to be effective.

Micro-generation devices such as rooftop solar panels, micro-turbines, wind power turbines, and fuel cells have become more affordable thanks to advances in technologies. One of the advantages of the smart grid is the use of these multiple distributed energy resources across residential areas. Moreover, the majority of customers within the smart grid will be equipped with electric vehicles (EVs) and other storage units. This allows consumers to choose between different sources of energy introducing flexibility and reducing the price as well as the load on the electric grid. In an environment where these resources are shared among users, an important question arises: How can these resources be shared in a fair

manner among the users given the heterogeneity of both resources and users.

These new components as well as the two-way flow of communication and energy, introduced by the smart grid, open the door for developing new approaches for load management namely advanced energy trading mechanisms. Besides reducing the load on the grid, which improves its efficiency and increases its reliability, they permit users to utilize clean energy resources, which helps in protecting the environment. From a consumer side, sellers make profit by selling their surplus of energy, while buyers minimize their energy bill by buying energy at lower prices.

Energy trading mechanisms need to tackle the different challenges stemming from the nature of the electric grid. For instance, the geographical distribution of sellers and buyers must be considered. The costs associated with transmitting energy through the grid's physical infrastructure need to be considered as well. The capacity of transmission lines connecting sellers to buyers also poses constraints on the amount and cost of energy to be traded. There is a need for energy trading mechanisms that contemplate the aforementioned constraints and provide profit to sellers and savings for buyers.

1.3 Thesis Objectives

In this thesis, we address the problem of load management using the functionalities provided by the smart grid. The main focus of this thesis is to promote energy savings and the use of clean energy resources, while providing users with incentives to participate actively in load management.

Our first objective is to manage the load generated by a set of appliances with different characteristics and types of energy demands. Our approach is based on minimizing the load and reducing the energy cost while taking into consideration users' comfort. The ultimate goal is to reduce the energy cost by shifting energy consumption from high load peak hours to low load non-peak hours. Moreover, consumers' privacy is addressed and incentives are provided to flexible consumers that accept changes in their consumption schedules.

Next, we consider load management within a microgrid where users share a set of

renewable, cheap resources. Providing monetary incentives is one of the main driving forces to users' participation in demand response programs. However, in the presence of shared resources with different costs, the question of fairness arises. We propose a demand response algorithm that fairly divides the costs of energy stemming from the use of the shared resources among the users.

Finally, we investigate energy trading mechanisms and the challenges stemming from their implementation in the smart grid. To provide an efficient energy trading mechanism, we propose a solution that takes into account the distribution of smart grid users, as well as the different constraints stemming from the nature of the physical smart grid infrastructure. In addition, we incorporate the different costs associated with transmitting energy through the grid's lines, and take into account their limited capacity.

1.4 Summary of Contributions

The following presents a synopsis of the major contributions presented in this thesis:

- Propose a load management model for different types of appliances, and a simple way to model user preferences, which is based on waiting time, type of appliance, and a weight factor to prioritize either comfort or savings. Both a centralized optimization model and a game theoretic approach are proposed to solve the load management problem.
- Propose a fair billing mechanism within a microgrid for load management that rewards users sharing common resources based on their contribution in achieving the overall system cost. The concept of the Shapley value is known for ensuring fairness. An approximation of the Shapley value is used to avoid the complexity problems that usually occur when calculating the Shapley value. We integrate this fair billing mechanism within a demand response program, which is able to balance the load and reduce the total energy cost by preventing peaks and rebound peaks from happening.

- Propose a model for energy trading within the smart grid. First, a centralized optimization model that takes into account the physical smart grid infrastructure constraints is presented. Then, a fully distributed game theoretic approach to trade energy among smart grid users is proposed. The goal is to minimize buyers' energy bills by allowing them to get economical and clean energy resources from their neighbors.

1.5 Thesis Organization

The remainder of the thesis is organized as follows:

Chapter 2 presents the related works and discusses the previous approaches to load management and energy trading in the smart grid. We also identify the issues and drawbacks of previous research and the different proposed solutions in the literature. Chapter 3 presents a user-aware load game theoretic approach for load management, which takes into account users' comfort. Chapter 4 presents a fairness aware game theoretic approach within microgrids. An energy trading mechanism that allows users to trade their excess of energy is presented in Chapter 5. Finally, Chapter 6 addresses the conclusions and future research directions.

Chapter 2

Survey on Energy Management in The Smart Grid

2.1 Introduction

This chapter presents a survey of current research efforts related to energy management within the smart grid. An overview of the major works addressing the loads stemming from Plug-in Hybrid Electric Vehicles (PHEVs) charging is first presented. Then, a detailed state of the art on the different load management mechanisms is cited where various solutions are illustrated. Billing mechanisms used in demand management are then presented. Finally, a detailed section on the various energy trading approaches in the current research is provided.

2.2 PHEV Demand Management

As the number of electric vehicles increases, the consequences of random and uncontrolled electric vehicles charging have been addressed in many papers. In fact, in [4] various charging strategies, such as quick charging and normal charging are analyzed and their effects within different time of the day on the distribution transformer are illustrated. The

authors in this paper concluded that as the number of PHEVs increases in the distribution system, the transformers, which are originally designed to handle overloading only for short periods of time, may break and cause grid failure. Then, they propose smart charging techniques, which require Automatic Metering Infrastructure (AMI) to monitor the residential loads, PHEV control unit, and remote switches. The first method is the stagger charge, where the load at the distribution transformer is continuously monitored by the PHEV control unit and compared with predetermined values. The PHEVs can be charged only if the overall transformer load is less than the predetermined value. In the other case, the PHEVs charging is deferred until the load is reduced to a value less than the threshold. The load control is the other method proposed, where continuous and real time monitoring of the loads generated by all the appliances within the house is required. The same mechanism is used in this method; the only difference is that instead of delaying the PHEVs charging, some other non-critical loads can be postponed so that the PHEVs can be charged.

The same approach is used by the authors in [5] where the status of the distribution system is considered to allow PHEV charging. In this paper, the authors have used two way communication between the central controller and PHEV units. They have proposed a PHEV admission control mechanism at the level of the substation based on the provisioned energy within the distribution system. They have also provided a theoretical analysis of this admission control technique by calculating the blocking probability of the various PHEV charging demands. They based their work on the assumption that the arrival of these demands follows a Poisson distribution and the service time of all PHEVs are identically and independently distributed as an exponential distribution. According to their results, their admission control is able to prevent grid failure since the number of blocked PHEVs increases within the system as the total amount of the requested energy exceeds the provisioned energy. In order to increase the system efficiency, the authors have extended the proposed admission control scheme. They have adjusted the number of customers accepted with the system by adding an activity factor that can tune the maximum power used by each PHEV in its charging process [6]. As a result, the overall energy consumption can be reduced even if low blocking probability is preserved within

the system. According to the authors, using this modification more users will be allowed in the system which will increase customer's satisfaction. However, by reducing the energy consumed by each PHEV, the total charging time required will increase.

2.2.1 Centralized Schemes

The authors in [7] have studied the relationship among load factor, variance and the feeder losses. They have developed three objective functions to minimize the losses, load variance, and to maximize the load factor. They showed that coordinated PHEVs charging could minimize the impact on the distribution systems. For an energy daily profile, they illustrated that the objective function based on the load variance or load factor are more useful than the one based on minimizing the losses as they yield to similar results but in reduced computation time and problem complexity.

The authors in [8] compare two control strategies, both of which are based on optimization. A local strategy schedules PHEV charging according to the loads of other appliances in a house, while the global one schedules PHEV charging taking into consideration global load information in a neighborhood. In the local strategy, the decision on when the car arriving at home will be charged is based on the current household load. A local energy controller takes decisions based on knowledge of energy consumption such as historical data and forecasts. On the other hand, the global control strategy is based on sharing knowledge amongst multiple homes, which requires some sort of communication and coordination to be present between homes. The goal is to reach a globally optimal solution for all homes. These strategies are compared to a business as usual scenario where uncontrolled charging is adopted in which vehicles are charged upon arrival to the home. Results show that the global method achieves a large reduction in peak load and load profile variability. The local strategy performs slightly less than the global one, however it still achieves better results than the business as usual scenario.

The authors in [9] propose an optimization-based solution to minimize both the operational and the PHEVs emissions costs. They propose a model that offers maximum utilization of renewable resources with integration of electric vehicles either as sources or

loads. Nevertheless, the availability and effectiveness of the renewable energy is influenced by various parameters including weather condition and the grid location. As result, charging the electric vehicles under these circumstances cannot be considered as a satisfactory source from the customers.

Similarly in [10], an optimal quadratic programming scheduler is proposed to solve electric vehicles charging by shifting the charging to non-peak hours when the demands for electricity is high. The PHEVs have to send their daily charging schedule to the central scheduler in order to determine the charging plans that are transmitted back to each PHEV.

Two strategies were proposed in [11] in order to optimize electric vehicles charging time and energy flows, based on price prediction and system auxiliary service. These solutions are implemented using deterministic dynamic programming methods. The PHEVs coordinated charging strategy is a centralized approach where the charging plan is calculated by a controller in order to find the state of the charge curve, which maximizes the PHEV's owner profit. In the same paper, the authors investigate the coordinated control of PHEVs as ways to generate additional profit by participating in ancillary service markets. At the same time, they analyze how these coordinated charging strategies reduce the effect of the uncertainties of the renewable energy resources on the overall power system.

The authors in [12] propose an optimization solution to schedule random PHEVs at corresponding nodes that can produce the minimum system stress, which impact the system reliability, performance, and security. The control strategy proposed is a real-time smart load management (RT-SLM). The RT-SLM is based on real time minimization of total cost based on integrating time-varying market energy prices and the favored charging time zones specified by each PHEV owner based on priority selection. The maximum sensitivities selection optimization method is used by the RT-SLM which allows the PHEVs to get access to energy as soon as possible by taking into consideration the users priorities and obeying the system constraints specified before, which maximize the grid operation performance.

In [13], the authors propose an intelligent method to be used in a regulated market in order to control the EV charging loads as a response to changes in the Time-Of-Use (TOU) price. An optimization charging model is first formulated to minimize the cost of

charging. Then, a heuristics approach is implemented to minimize the cost of charging while considering the relationship between the state of charge of the EVs battery and its acceptable charging power. Finally, the authors compare the energy demand and the charging cost in different intervals of time and compare them for optimal and typical charging patterns. The results illustrate the effectiveness of the optimized charging pattern in reducing the cost of charging and flattening the peak load.

In [14], the authors propose a PHEV charging scheme to reduce the system cost while maintaining reliability. The scheme permits an aggregator to allocate charging in a way that minimizes the overall system costs of steady state and ramping. Two competing cost objectives result from the high cost of ramping generators at peak-load and the traditional cost stemming from steady-state operation. In comparison to uncontrolled charging, the proposed intelligent scheme helps reduce the whole system cost by up to 16%.

In [15], the authors propose the use of an aggregator to manage electricity market participation of a vehicle fleet. A framework for optimally charging and discharging electric drive vehicles based on the fleets driving patterns and variations in electricity market prices is then proposed. Two optimization functions are presented depending on whether the aggregator is price-taker or has market power. In the former case, the optimization can be formulated in terms of linear programming, while the latter requires a quadratic programming formulation. Data from a Danish case study was used to construct representative driving patterns and to predict electricity price variations. Finally, results show that EVs provide a level of flexibility exclusively through charging.

In [16], the authors show how existing power networks and equipments can be better utilized by controlling the rate of charging of EVs. Similar to many other works, the authors chose to apply linear programming to find the optimal charging rate for each EV in order to maximize the total power delivered to EVs without exceeding the limits of the network. The proposed technique was tested on a residential distribution network and the results demonstrate that high penetration of EVs can be achieved by controlling their charging rate, without the need to upgrade existing network infrastructure.

The authors in [17] propose an algorithm to manage the charging of a large number

of PHEVs (around 3000) in an optimal manner. The authors propose the use of the estimation of distribution algorithm to allocate energy to PHEVs in an intelligent manner. They also provide a mathematical framework for the objective function which maximizes the average state-of-charge at the round time. The proposed algorithm was evaluated using simulations that considered real-world constraints including the price of energy, the remaining battery capacity, and the remaining time to charge. Real-world transportation data was also used to simulate a real-world parking deck. The proposed algorithm was contrasted against other optimization techniques and showed to be more effective compared to more traditional methods.

In [18], the authors study the problem of optimizing the charging pattern of PHEVs, which is defined as both the time and rate of charging PHEVs from the electric grid. The optimization objective is to minimize both the overall cost of fuel and electricity, as well as minimize battery health degradation over a driving cycle of 24 hours. These optimization objectives are contradictory as the authors show. Results show that to minimize battery degradation and energy cost effectively, PHEVs should be charged ideally over a short period of time, during off-peak hours, and right after the onset of road travel. Although results were obtained using a specific type of PHEV batteries, the authors claim that the presented methods can be generalized to other degradation models and battery types.

In [19], the authors propose a smart approach for load management to coordinate multiple PHEVs chargers in a distribution system. The objectives involve shaving the peak demand, improving the voltage profile, reducing power losses as well as the impact of charging stations. Daily residential loading patterns were used as constraints to the objective function.

2.2.2 Decentralized Schemes

In [10], a multi-agent system is proposed to solve the scalability and the dependency problem on the exact behavior of PHEVs related to the optimization solution. The multiple agents have to negotiate between each others in order to find a mutual charging plan that does not overload the system. The authors propose two coordination mechanisms. The

first one is based on energy reservation where household loads forecast are needed. The other scheme is a power limiter where no forecast data is required and a low pass filter is used to charge the PHEVs. The main problem with this last mechanism is determining the cut-off frequency beforehand. Finally, the multi-agent system requires more evaluations in order to see the different results and how the system behaves in various situations and under multiple settings.

The authors in [20] apply and extend methods from mechanism design and stochastic optimization fields to incentivise strategic EV agents to truthfully reveal their preferences and coordinate charging for effective EV charging. In generic terms, the problem can be described as real time scheduling of EVs sharing a common scarce resource over time, which require a certain amount of charge by their departure, and given the uncertainty about any arrivals in the future. The authors base their solution on a widely used heuristic approach in stochastic optimization, namely the Consensus approach. In order to elicit agent's preferences, the authors introduce the concept of pre-commitment which causes the mechanism to pre-commit to charging a vehicle by its departure time whenever an agent gets selected. This scheme maintains flexibility about the time and rate of the charging. The effectiveness of the proposed scheme is evaluated against the optimal solution using simulations.

The authors in [21] proposes a decentralized algorithm to schedule EVs charging in an optimal manner. The authors exploit the elasticity of EVs loads in order to fill the valleys in load profiles. An optimal control problem is first formulated for the EV charging scheduling problem, where the objective is to impose a generic notion of valley-filling. The authors study the properties of optimal charging profiles. A decentralized algorithm is then proposed to solve the optimal control problem in an iterative manner. During each iteration, each EV updates its charging profile according to the control signal received from the utility company. The utility company changes the signal for each iteration in order to guide the EVs updates. The authors then show that the algorithm converges to the optimal charging solution regardless of the specifications of the EVs, and even if they do not update their charging profiles within each iteration, or use an outdated control signal

when they do update their profiles. In addition, each EV needs to solve an optimization problem locally, which requires high computation and processing power.

In [22], the impact of the mass operation and electricity consumption of EVs and PHEVs on the distribution network, specifically on transformers is studied. Simulations of Lithium-Ion batteries and transformer loss of life are developed. The evaluation of transformer loss-of-life is made using discrete information for the battery, charger and time of arrival. Simulation results show that power management of EV charging profiles can help to better manage the loss-of-life of distribution transformers. The authors present two approaches for scheduling EV battery charging and show that coordination between charging stations can avoid unnecessary transformers loss-of-life due to EV charging.

2.3 Residential Demand Management

In the past few years, residential load management in the smart grid has seen major interest from researchers as environmental and energy conservation concerns are growing worldwide.

Demand management is a key component of the smart grid as it enhances grid reliability and efficiency. To attain high level of robustness, the traditional electric grid is usually designed to handle peak demands instead of average demands, which can result in underutilization of the system [23]. Various demand management programs are used to substitute the old operational way in traditional grids where the utility companies are required to match supply to the demand. These techniques can adjust users' behaviors so that the available supply of energy is used efficiently, which enhances the overall grid reliability. As stated in FERC staff report [24], demand response mechanisms can be classified into two general categories. First, time-based programs use different types of time differentiated price signals to encourage users to reduce their loads individually. For instance, the Critical Peak Pricing (CPP) pushes users towards reducing their consumptions during peak hours. On the other side, in the incentive-based mechanisms customers receive some kind of load control messages from the utility. Some kind of incentive based payments or

promised arrangement between the customers and the electric utility are used in this category. Direct load control, interruptible load, and load as capacity resource are types that fall into this category [25]. They can provide high peak load reduction as they encourage users to achieve high savings by shifting their loads. The other classification that seems more related to our work is based on the way these schemes operate. In this thesis, we classify demand management into three major categories: centralized, decentralized, and user-based.

2.3.1 Centralized Schemes

In [26], the authors first propose an in-home optimization technique to minimize the customer's cost. Using a set of simulations, they showed that if all residential users are given the same dynamic price, the home energy controller within each home will instantaneously reschedule the load from the high price period to the low price period. Thus, instead of removing the peak and lowering the cost, a new rebound peak is created.

In [27] the authors propose an optimization-based model to calculate the optimal day-ahead appliance scheduling under hourly pricing and peak power-limiting based demand response strategies. Similarly, In [28] the authors formulate an optimal control of electricity consumption as a convex programming problem to minimize electricity payment and waiting time under real time pricing.

The authors in [29] presented a technique to manage the integration between energy production, consumption, and storage. This methodology is based on three steps. First, a neural network-based prediction approach is used to predict the demands and the production of the next day. Then, the local controller within each house aggregates the energy profiles and sends them to a global controller. Within the second step, a tree structure is used to aggregate the energy profiles and the global controller iteratively determines an appropriate incentive signal to reach a global objective. As a result, the planning for each house is determined for the upcoming day. In the last step, a real time control algorithm, based on the signal received from the global planning, determines the time when and which appliances are turned on or off, when and which generators are turned on or off, and how

much energy flows from and to the buffers. It is true that the global planning is centralized but results show that good local predictions lead to a better matching of demand and supply.

The authors in [30] describe a decision support tool for smart homes where a PHEV, space heater, water heater, pool pump and generation of the PhotoVoltaic (PV) system are scheduled using various time of use tariffs. A co-evolutionary version of particle swarm optimization technique is used for scheduling the available distributed energy resources in order to maximize the benefits of the owner from the smart electrical energy services.

A generic architecture of energy management systems in a home area network is proposed in [31] in addition to an efficient scheduling method for home power usage. The home gateway receives demand response information representing the real-time electricity price and transfers it to an energy management controller. This latter uses demand response to achieve an optimal power scheduling scheme to be forwarded by the home gateway to each electrical home appliance. The Real Time Pricing (RTP) model could cause damage to the electric grid when most appliances operate during the time with the lowest electricity price. This is why the authors combine RTP with the Inclining Block Rate (IBR) model to effectively reduce the cost of electricity and the peak average ratio, reinforcing the grid's stability. A genetic algorithm is adopted to solve the optimization problem because of its nonlinear property.

The authors in [32] discuss an algorithm for automatic demand response and energy scheduling in order to flatten the aggregate demand load. They demonstrate that the utility company has a low cost when it experiences a flat usage of energy over a period of time. The rebound effect is also demonstrated which might happen after a demand response event. The proposed algorithm is formulated as an optimization problem where optimality is proven using Karush Kuhn Tucker (KKT) conditions. However, the authors do not consider load models and operating constraints of practical appliances such as water heater, and cloth dryer, in their mathematical algorithm. The impacts of the proposed optimal load scheduling algorithm on the comfort of users' as well its applicability in real-life were not considered by the authors.

In [33], the authors explore the idea of indirect control of the consumption level of household appliances based on price signals sent to customers. Prices are first estimated and then broadcast every day for the next one so that households optimize their consumption by altering the schedule of their appliances. Using a data-driven statistical approach, the consumer's elasticity is estimated and forecasted using data measured at the grid level, eliminating the need for sensors and communication devices between customers and the price-generating device. The price-response model enables the prediction and simulation of electricity consumption under different pricing scenarios coupled with uncertainty. Forecasts are embedded within a chance constrained optimization framework that explicitly accounts for uncertainty and for pre-determined maximum allowed consumption levels. The goal is to maintain the price signal unchanged from the market price while maintaining consumption under a specific threshold.

The authors in [34] propose Cloud Demand Response (CDR) architecture for achieving fast response times in large scale smart grids using clouds. CDR uses data-centric communication, publisher/subscriber and group communication to secure demand response and make it scalable and reliable. The proposed architecture appears to the grid as a black box that takes input from the utility such as power deficit, and gives back information about the customers such as power reduction and the resulting price incentives. The authors propose two distributed optimization algorithms that are market-based to optimize power usage of appliances, namely the bisection and Illinois methods. The proposed architecture and distributed algorithms are evaluated through simulations.

The authors in [35] propose a method for load control based on consumers' elasticity of electricity price. Load control is caused by a need from the supplier to reduce the load. An optimization problem is formulated as the minimization of the cost to consumers subject to constraints such as the maximum load reduction of a consumer, maximum electricity price increase, and the balance in both the load and generation. Particle swarm optimization was used for solving the optimization problem.

A simulation tool for optimized operation of household appliances in a demand side management system is presented in [36]. The main goal of the simulation tool is to demon-

strate customer focused demand side management operation, and estimate home power consumption while minimizing the customer electricity cost. An optimization algorithm based on particle swarm optimization is used to optimize the operation of the tool.

In [37], Distributed Energy Resources (DER) are considered in the formulation of an optimization problem to minimize the operation costs of a virtual manager that manages resources in the DERs for a given time period and the energy available from external energy sources and suppliers. A modified version of particle swarm optimization using Gaussian mutation of the strategic parameters, and self-parameterization is used to solve the optimization problem.

A third party that manages energy consumption of a group of users is introduced in [38]. Hence, the load scheduling problem is formulated as a constrained multi-objective optimization problem. The main optimization objectives are to minimize energy consumption cost and maximize a specific utility. These goals can be conflicting and non-commensurable. Two evolutionary algorithms are developed to solve the optimization problem and obtain solutions to the constrained multi-objective optimization problem. The proposed algorithms are evaluated using extensive simulation results.

The authors in [39] propose the use of a heuristic based on the Longest Processing Time algorithm to minimize the maximum user bill for each time slot, rather than on a daily basis. The effect is that even though the user's daily bill is not minimized, his demand curve can be effectively flattened.

Another optimization model is presented in [40] to adjust the hourly load level of a particular consumer in response to changing electricity prices. The goal of the optimization is to maximize the utility of the consumer subject to certain constraints, namely minimum energy consumption per day, maximum and minimum hourly load levels, and limits on these load levels. Robust optimization techniques are used to model uncertainty in prices and the proposed model turns into a simple linear programming algorithm, which can then be integrated easily into an energy management system in small businesses or in households. The proposed model requires a bidirectional communication device linking the customer and utility.

In [41], mixed-integer programming is used to model appliances and subscribers conditions and constraints. An optimal power consumption schedule is calculated based on dynamic pricing information to balance user satisfaction and the overall energy cost. In addition, renewable energies and energy storage systems are integrated in the problem formulation. In order to cater for scalability issues, a parallel distributed algorithm is proposed where a demand response coordinator and subscribers solve sub-problems on their own in a coordinated manner. Robust optimization techniques are used to accommodate the randomness in electricity prices and in renewable energy generation.

The authors in [42] propose the use of a third party that manages the load of a group of customers by formulating load scheduling as a constrained multi-objective optimization problem. The objectives of this optimization is to minimize the energy consumed as well as maximize a given utility. To solve this problem, the authors propose two evolutionary algorithm that are evaluated using extensive simulations. Similarly in [43], a heuristic based evolutionary algorithm is proposed to solve the minimization problem based on load shifting technique.

In [44] the authors propose an electricity load scheduling algorithm that controls the scheduling and energy consumption of appliances to maximize the net utility of a residence while taking into account its budget limit. Appliances are classified into different sets depending on the energy consumption and the operation characteristics. The optimization problem is formulated as a difficult to solve Mixed Integer Nonlinear Programming (MINLP) problem. The generalized Benders decomposition approach is used to solve the MINLP problem easily with low computational complexity.

A different approach that consider cloud resources is presented in [45]. This approach illustrates a novel cost oriented model that targets the concept of using cloud based resources for demand side management applications. This cost oriented optimization model considers the uncertainties associated with this kind of application such as computation loads prediction errors. To solve this optimization problem, a modified priority list algorithm is formulated.

2.3.2 Decentralized Schemes

In [46], a heuristic neighborhood level energy management mechanism is proposed to schedule the households' demands in a residential area. This distributed algorithm is based on the fact that the total load must be less than a maximum power allowed by the grid while at the same time the grid guarantees a minimum power that is available all the times for each home. However, all the Energy Management Controllers (EMCs) within the homes must compete for any additional power using the common control channel, where a mechanism similar to access control methods is used. Its main purpose is to randomize the EMCs access to the total generated power. More precisely, the EMC sends a request before using the electricity and calculates the remaining available power based on the amount of energy used by all the houses before accepting the given load. This proposed solution can alleviate the peak problem but it needs very reliable communication schemes and it might result in a waste of energy when the minimum power allocated for each user is not needed. Finally, the proposed scheme requires synchronization which sometimes can be hard to achieve.

The authors in [47] focus on balancing the overall load and reducing the peak-to-average energy consumption ratio in a given neighborhood. They illustrate that developing a demand side management based on the aggregate load of the users, rather than the individual user's consumption, offers better savings. In this scheme, the users are required to coordinate their energy usage using the communication technologies enabled by the smart grid. All the residents of this neighborhood find an optimal consumption schedule by playing a game based on an optimization technique. Even if the optimization-based resident load management programs achieve efficient energy and cost saving, the users' individual preferences and priorities are not taken into consideration.

Similarly in [48] a game-theoretic energy schedule (GTES) method is proposed to decrease the peak-to-average power ratio through optimizing the energy schedules of the consumers. This method is based on the interaction between a power company and the consumers where each consumer is first pulled by the power supplier, in a round-robin manner, and provided with the energy price and the actual energy consumption vector. Then, this user will optimize his own energy schedule and send it back to the supplier that

will update the energy price and continue pulling the other consumers.

In [49], a novel control scheme is proposed for automated demand response mechanisms. Experimental research and computer simulations are used to demonstrate the scheme, which considers a decentralized control structure, automated functions, distributed intelligence, and a uniform representation of heterogeneous resources. It also captures operational planning, energy as well as service provisioning, and financial settlement.

A Stackelberg game is proposed in [50] for the purpose of effectively reducing power generation costs as well as consumers' electricity cost. The proposed game takes place between different utility companies and different end users, each of which tries to achieve the maximum profit and payoff, respectively. Analytical results for the Stackelberg equilibrium of the game are derived proving that a unique solution exists. A distributed algorithm is then developed which converges to the equilibrium using only local information that is available from both end users and utility companies. Finally, the authors study the impact of manipulating the electricity price by attacker on the reliability of the grid. A scheme based on the concept of shared reserve power is proposed to tackle this challenge and improve the grid's reliability and dependability.

Likewise, in [51] the authors propose a real-time price-based demand response algorithm to calculate the optimal load control of devices. The interaction between the energy provider (leader) and devices (followers) is formulated as a one-leader, N-follower Stackelberg game. Each player forms an optimization problem to help in selecting the optimal strategy.

In [52], the authors describe a demand side management mechanism that can reduce energy consumption peaks as well as carbon emissions. The household loads are divided into two shiftable loads and thermal loads. The first optimizing agent is minimizing the cost and the deferment of shiftable loads based on the price that is received by each smart meter. For the thermal loads, an intelligent adaptive thermostat is used to optimize the heating or cooling profile. The authors first showed that the uncoordinated optimization algorithm where each user individually reacts to the price of the electricity can result in poor system performance. Then, they modified the optimization technique into a centralized one where

the cost of electricity is based on the aggregate demands rather than the predicted price by each user. They proposed adaptive mechanisms for agents so that they can coordinate without any centralized control. This mechanism is based on Widrow-Hoff learning where agents gradually defer their loads according to a deferment parameter toward the calculated optimal solution in order to remove the rebound peaks. Also for the same purpose, the thermal load profile is re-optimised with a given probability.

Game theoretic frameworks are proposed in [53] for demand response at both electricity markets and consumer levels. First, the authors model the interaction between a demand response aggregator and electricity generators as a Stackelberg game. The aggregator acts as the leader of the game and makes demand reduction bids, while generators act as followers that compete for maximizing their profits based on the reduced demand. Then, the interaction between the aggregator and consumers is modeled as a mechanism design problem. The goal for the aggregator is to minimize the aggregate inconvenience of consumers while achieving the targeted load curtailment.

In [54], a hierarchical system model that includes multiple energy providers as well as a large number of consumers within smart grid is proposed. A Stackelberg game is played between energy providers and end users in order to maximize the customers welfare, which act as followers, while the leaders (energy providers) maximize their earned profit. The authors prove the Stackelberg equilibrium of the game and illustrate that the providers profits is increased by having large number of providers.

In [55], the authors propose a real time demand side management system. First, a centralized scheme that minimizes the peak to average ratio as well as the power generation cost is proposed. Then, a game theoretic approach is presented to motivate customers to participate in the demand management such as preserving privacy since all the computations are done locally.

In [56], the authors focus on controllable load types associated with dynamic systems that can be modeled using differential equations. A two-level differential game framework is proposed. The upper level (aggregator, utility, or market) decides the price given the demand at the lower level. Then, each player (residential or commercial buildings) at the

lower level controls its electricity usage and schedule to minimize its energy bill.

In [57], the authors apply a class of non-cooperative games, called the congestion game, in order to perform dynamic pricing to control the power demand. The ultimate goal is to achieve energy savings and efficiently utilize the available energy. The authors discuss the key characteristics of using the congestion game for demand side management and show that equilibrium can be achieved by means of a distributed algorithm.

The authors in [58] formulate a cooperative demand response scheme for load management as a constrained optimization problem that generates Pareto-optimal response strategy consumer profiles. Moreover, they develop an incentive-compatible trigger-and-punishment mechanism to avoid the non-cooperative of selfish customers. A cluster based method is used to transform the social optimization problem into multiple suboptimization problems, where the cooperative demand response is executed at each cluster head.

A dynamic pricing scheme that provides users with incentives to adjust their power usage in order to achieve a flat overall power consumption is proposed in [59]. Since finding an optimal schedule is a NP-hard problem, the authors present methodologies that study how close one gets to the optimal solution. Considering privacy concerns, customers are not obliged to share their energy consumption behavior and might choose to only share part of the information. Hence, the authors consider both cases where customers are willing to share all or only part of their load profiles. Different scheduling policies are studied and compared, namely uniform, ALOHA I, ALOHA II, and Time/Slackness.

In [60] the authors propose a pricing algorithm to minimize the peak-to-average ratio in aggregate load demand. The challenge addressed is the energy provider's uncertainty about the impact of prices on users' load profiles. An iterative stochastic approximation approach is used to design two real time pricing algorithms based on finite difference and simultaneous perturbation methods.

A new scheme called Demand Response Exchange (DRX) is proposed in [61] as a separated market for trading demand response in a fair and flexible manner among all beneficiaries. This concept was introduced by the authors after studying different demand response scheduling schemes which have shown to be inefficient due to externalities that

happen between beneficiaries including the transmission, distribution, and retail networks. DRX is an integrated market where consumers compete to sell demand response services in terms of load reduction and get money in return. A DRX operator coordinates the financial transactions between selling consumers and buyers using appropriate market rules and functions to maximize efficiency among different participating parties.

In [62] the authors consider households operating multiple appliances including batteries and PHEVs and propose a demand response scheme based on utility maximization. Every household appliance is regarded to provide some benefit based on the pattern or volume of electricity consumed. Hence, each household tries to maximize its individual net benefit by scheduling power consumption in an optimal way subject to different consumption and power flow constraints. The authors show that time-varying prices that align individual optimality with social optimality exist, meaning that when such prices are enforced, households optimize their own benefits in a selfish way and automatically contribute to maximizing the social welfare. Therefore, dynamic pricing can be adopted by the utility to coordinate demand response and benefit the whole system. Finally, a distributed algorithm is proposed for both the utility company and consumers to compute optimal prices and demand schedules together.

In [63], the authors propose a distributed framework demand response based on cost minimization. Each user finds an optimal start time and operating mode for the appliances in response to the varying electricity prices. An approximate greedy iterative algorithm is proposed for each user to schedule appliances.

A different approach for demand management is proposed in [64] that targets both optimality and scalability. It is based on the Lagrange relaxation approach, which decomposes the demand response optimization problem into individual subproblems solved in a decentralized way. Likewise, the authors in [65] propose a distributed system wide demand response management model with the goal of flattening the total load profile, which is subject to minimum individual cost of customers. First, the model is formulated as a bi-level optimization problem, and then casted to equivalent single-level problems. These latter are solved using an iterative distributed algorithm.

In [66], the authors propose a distributed optimization algorithm based on the alternating direction method of multipliers to solve the optimization problem. Customers only need to report their aggregated loads to the utility company, which preserves their privacy. In order to speed up optimization computing, customers can update their loads scheduling simultaneously and locally. In [67], the authors present a fast-converging distributed algorithm for EVs to manage their charging and shape the daily demand profile, and minimize the system's peak demand. To model the random and realistic behavior of EVs, random distribution functions are assigned for EVs' arrival time, charging time, and departure time.

The authors in [68] propose an approach for managing a fleet of electric vehicles, consisting of three steps: aggregation, optimization, and control. First, at the aggregation level, a tree is used to combine PHEV charging constraints. Then, in the optimization step, a collective charging plan is computed using these aggregated constraints with the objective of minimizing the energy generation cost. Finally, within the control step, an incentive signal is created for all PHEVs based on the computed charging plan.

Other works have considered smart grid users with load prediction capabilities. For instance, the authors in [69] present a distributed demand management approach based on day ahead bidding as well as the real time adjustments for changes in user needs and production.

Unfortunately, the savings achieved in energy consumption and price reduction do not always reflect a high user comfort. For example, an air conditioner that is scheduled to start at a certain time should not be delayed to save energy if this would make the user feel uncomfortable due to the imperfect room temperature.

2.3.3 User-Based Schemes

The authors in [25] first present a demand response framework which could be implemented within a home area network. Within each home, a Home energy Management System (HMS) is used as a central monitor that takes all the energy decisions, while appliance interface units are used for communicating with HMS. They also propose a demand

response mechanism to control energy intensive loads taking into account users' comfort and load priority. The users have to set first their load priorities so that the HMS can manage the loads based on the control signal received from the electric utility. This way the HMS will start by reducing the energy consumed by lowest priority devices and move up to higher priorities until the designated demand limit is reached. Similarly, in [70], a home energy management algorithm is proposed to manage the power consumption of household appliances based on their priorities by ensuring that the consumption is always below preset levels.

In [71] the authors propose a peak-to-average ratio constrained energy scheduling scheme for household appliances. The optimization problem aims to minimize energy cost by determining the optimal power usage and operating time of appliances. They then introduce a multi-objective optimization problem that also minimizes the inconvenience posed to customers due to the shifting of their appliance schedules. Both centralized and distributed approaches are proposed to solve the above mentioned problems.

A scheme based on congestion pricing and quality of service concepts in TCP/IP networks is proposed in [72] to manage residential load in a distributed manner. A user utility function is used to determine each consumer demand in the next time-slot. The adaptation mechanism used in this scheme is based on the current price and a Willingness To Pay parameter (WTP) that changes the behavior of the system and controls users demands. However, the WTP parameter is introduced as a way to impact the price and to show the interests of the users in getting the energy rather than modeling the user preferences or comfort, such as the appliance scheduling delay or the waiting time. In addition, the system has no feedback loop that permits continuous monitoring and intervention.

In [73], a scheduling problem based on optimization is proposed to balance the total load and minimize the user inconvenience produced by the demands scheduling. The discomfort level of users is modeled as preferences set by the users themselves. This requires users to manually set a preference matrix which specifies exactly the preferences for each appliance as well their rank. Details on how such matrix can be populated are not discussed by the authors. Similar work is proposed in [74] where a system that helps users to react to real

time electricity prices but at the same time preserves their lifestyles. The optimization engine is using the preferred profile as a reference and produces several energy schedules which try to minimize both the energy cost and the users inconvenience. In this paper, as opposed to [73], the user preferences are inferred from the data collected from the jPlugs, which are sensing units that continuously monitor the energy used by each appliance. As result, better information about usage configurations and operating features are provided compared to the ones set manually by the customers. Within [73], the purpose is to minimize the energy cost and balance the total load while in [74] the main concern is to schedule the appliances within one house based on the predicted energy prices.

In [75], the authors tackle the problem of overloading at the level of the distribution transformer due to EVs penetration. The proposed solution is based on a load shaping tool that introduces load control strategies inside the household by taking into account pre-set users preferences and priorities. In fact, the distribution transformer monitoring system sets the demand limit for the house. Then, to make the overall load below this demand limit; the home energy within each house management tools manage the household loads according to their priorities and the customer comfort levels. They showed that the system upgrade can be prevented using the demand limit on customers. However, setting the demand limit on each house to avoid the overloading is not an easy task especially with various customers' needs. As an extension to this work, the same authors have proposed a demand response program that focuses on the impact of EVs charging on the residential distribution circuits where the customers have the ability to decide which load to control and when [76]. In this extension, multiple comfort indices, such as severity, scale and duration, are proposed in order to calculate the effect of the demand response program on the customer life style.

In [77], the authors propose a hierarchical multi-agent control system to reach a high level of users comfort and at the same time to reduce energy consumption in microgrids. The central coordinator agent is used to coordinate among all the agents, switch agents, local controller agents, and load agents to realize the main goals. The comfort index is a composite parameter that models the users comfort as function of environmental

temperature, illumination level, and indoor air quality. A particle swarm optimization technique is embedded within the central coordinator agent to maximize the comfort index. In addition, all the other appliances within the house are considered as noncritical and interruptible loads, which may not be realistic. For instance washing machine and electric stove work in cycles and cannot be interrupted. The comfort is limited to only three parameters: air quality, thermal, and visual comfort.

The authors in [78] propose a load-scheduling protocol based on communication for home appliances that are connected through a Home Area Network (HAN). The goal of the protocol is to enable appliances to coordinate power usage to keep the total energy demand for the whole home below a certain threshold value. The protocol considers both flexible appliances which can be scheduled with some delay, and critical appliances which use power as they wish. The energy management controller uses an optimization formulation to decide on the amount of energy during each time slot based on the variation of energy prices as well as distributed wind power uncertainty. The protocol is studied as a two-dimensional markov chain to quantify the average delay of each appliance. The authors use simulations to show the cost savings obtained using the proposed protocol.

A Home Energy Management (HEM) algorithm is developed in [79] to guarantee that the total household demand does not exceed a specific threshold at any instant during a specific duration. HEM uses the notion of priorities to enable users to set the priority level for different appliances so that they are considered by the algorithm. The authors consider different preference settings of users using the following appliances: water heater, air conditioner, clothes dryer and electric vehicles. HEM is an incentive-based protocol that determines load reduction based on a signal from the utility provider. The algorithm is evaluated through simulations and the results show that it can limit the total household demand given that users make some sacrifices in terms of their comfort.

In [80], the authors discuss a scheduling model to control the peak load which is made of three modules: an admission controller, a load balancer, and a demand response manager. To minimize the peak load demand, power loads are divided into three categories depending on their load characteristics. Baseline loads represent power consumption of

appliances that are inflexible. Burst loads represent consumption of appliances that run for a fixed time interval and are turned on and off within a given deadline, such as washers and dryers. The third type of appliances is regular loads which represent appliances that are always running for a long period of time such as refrigerators. Demand-side management is achieved through three main layers, admission control, load balancing, and demand response management. The authors propose the use of different existing demand-response schemes to their proposed architecture and evaluate its performance using Matlab simulations.

In [81], the authors propose to decouple utility cost minimization and customer satisfaction in terms of social welfare maximization into two stages. The decoupling, explain the authors, is the result of seeing the utility as risk averse in real life as opposed to the traditional risk neutral approach used in other works which combine the two objectives in a single weighted sum. First, a convex optimization problem is formulated to minimize the utility's cost of generation and operation delay. A load management scheduling approach in the form of water-filling is derived analytically to calculate optimal schedules. Based on these schedules, the authors use repeated Vickrey auctions to allocate load demands across different customers to maximize the social welfare. In order to make the Vickrey auction more robust to untruthful bidding, the authors suggest introducing a reserve positive price and evaluate their two steps model through simulations.

The work in [82] distinguish itself from other residential load scheduling schemes which are centralized, based on optimization, and use day-ahead pricing or predicted price. Instead, an opportunistic scheduling scheme which is based on the optimal stopping rule is proposed as a real-time distributed scheduling algorithm for automating smart appliances' control. It provides the best time for appliances to run in order to provide a balance between the electricity bill and inconvenience stemming from delaying the operation of appliances. The authors show that when no constraints are considered, the proposed scheduling algorithm is a distributed threshold policy. However, when a total power constraint is introduced, the scheme can be implemented in a centralized or distributed manner.

In [83], real-time price-based demand response management for residential household

appliances is evaluated using stochastic optimization and robust optimization techniques. The proposed real-time price-based demand response management application can be integrated in smart meters and executed online to establish the optimal operation of residential appliances within 5-minute intervals taking into account uncertainties in real-time electricity prices. The different types of appliances considered are deferrable, non-deferrable, interruptible and non-interruptible appliances based on their spatial and temporal characteristics. The proposed stochastic optimization approach is based on a scenario and uses Monte Carlo simulations to minimize the daily expected electricity bill while controlling the risk related to real-time electricity price uncertainties. Uncertainty intervals are considered in the robust optimization approach to minimize the worst-case electricity bill as the robustness of the solution is adjusted in a flexible manner. Mixed integer linear programming is used to model both optimization approaches and state-of-the-art solvers are used to present results of the optimizations.

The authors of [84] propose an approach that is based on communication protocols to decrease the power demand so that power consumption is uniform over time. Power consumption is divided into two types of loads: real-time and schedulable. A target power level is defined so that the proposed algorithm schedules power in a way that the target is not exceeded. The algorithm consists of three major phases: a power update phase, a power request phase, and a power scheduling phase. Simulations of the proposed scheme show that the power demand can be kept below the defined threshold level.

In [85] the authors propose a reward based demand response algorithm to shave peaks. Customer rewards are allocated to customers based on load shift and voltage improvement stemming from load adjustment. The proposed algorithm allows to reduce peak demand and achieve customer satisfaction.

A dual decomposition approach is presented in [86] to manage residential loads with different energy requirements in a distributed manner. This is achieved by exchanging Lagrange multipliers and hourly consumption data between the utility company and the consumers. In addition, a disutility function that maps the amount of power used to a satisfaction level is used to model the user's satisfaction. Similarly, in [87] a sigmoid

function is used to model the comfort of the users in terms of the amount of power used by an appliance.

A home energy management scheduling approach is proposed in [88] that considers household comfort constraints. It basically requires the user to specify their tolerance to changing the appliance use time; however, the only purpose is to minimize the energy cost without taking into account the effect of this tolerance on the user's comfort.

In [89], a joint optimization of both electric vehicle and household load scheduling is proposed. The main objective in this optimization is to minimize the energy cost while taking into consideration user comfort and using the electric vehicles as storage facilities. The comfort preference is modeled by considering thermostatically controlled appliances only, where each user needs to provide the preferred temperature and the maximum acceptable deviation.

In [90] the authors propose a decentralized system-wide framework to coordinate demand response of residential customers. The objective is to modify system load profile provided that customers' payments are minimized, and their comfort and privacy are preserved. The energy provider iteratively exchanges load information with the customers in the hope of achieving his desired load profile. Customers take into account their financial and comfort constraints, to send back load reschedule proposals to modify system load profile. Received proposals that improve system load profile are accepted by the provider and applied. Comfort is modeled as the appliance start time chosen by the customer.

In [91] the authors present a mixed integer nonlinear optimization-based home energy management system, that integrates different classes of appliances and considers the user's comfort, which is modeled in terms of volume of energy curtailment. Dynamic price signals are used to control the operation of appliances and reduce the bill. The optimization problem is solved in an iterative way through the day as energy prices and controller inputs change.

The authors in [92] propose a work that focuses on studying the trade-off between achieving the user comfort and the electricity payment. The user comfort is modeled as waiting time that is associated with a cost. The approach is based on optimization where

the waiting time or the energy cost is minimized using a knob parameter.

2.4 Fairness within Demand Management

As illustrated in the previous section, demand response programs are used by the utilities companies to manage the energy consumed at the level of consumers side. Basically, the majority of demand management approaches focus primarily on achieving a given system objectives such as minimizing peaks and decreasing the total cost of power generation. In this section, a state of the art of the works that have studied fairness within demand management is illustrated.

Various pricing schemes for demand management have been proposed in the literature. For instance, a flat rate scheme bills all users with a fixed rate regardless of time of day. TOU pricing scheme charges rates that are fixed, predetermined, and depend on the time of day such as off peak rate and on peak rate. A different scheme is Real Time Pricing (RTP), where consumers are billed dynamically depending on the market clearing price. In general, RTP is an hourly rate but in some cases it can be applied for a period less than an hour depending on the energy usage. More details can be found at [93].

In [94], a pricing mechanism is proposed to coordinate energy delivery for delay tolerant demands. A transaction is first defined as the process of delivering an amount of energy to a given user under a given power trajectory and time constraints. The users have to send their requests to a central scheduler that bills them according to the amount of energy requested, the flexibility, the current market prices, and the congestion at the level of the distribution network. The decision made by the scheduler is based on minimizing the total energy cost under the market uncertainties using dynamic programming. The proposed mechanism protects the distribution feeder from the overloading and offers various gains to users but it is centralized and may need excessive calculation.

The authors in [95] propose a fair demand response and compare it with existing pricing schemes. They have defined two pricing schemes depending on the type of user and the type of appliance, fixed charges pricing and multi-dimensional differential pricing. The

fixed charges pricing is applied for “must run” appliances that the consumer must use such as lighting. Multi-dimensional differential pricing scheme charges the users based on multiple dimensions. First, the rate depends on the user category, which refers to the type of consumer such as residential user or industrial one. This pricing scheme also charges depending on the type of appliance, “must run” or “optional run” such as heater and washer. The income level, which refers to the ability of the consumer to pay, is also included in this pricing scheme. This fair demand response is based on an optimization solution with the objective of maximizing the profit of the utility company while considering the previously defined pricing schemes.

A mechanism that schedules users’ load using water-filling method is proposed in [96]. In particular, distributed schedulers are used to allocate time slots for soft loads based on pre-calculated and pre-distributed demand forecast information. The scheduling method allows users to shift some loads to off peak hours, which results in a flat and relatively constant power demand profile. This yields to an efficient system with a uniform pricing scheme. Fairness in this context is used as a factor that specifies the willingness of users to adopt the scheduling algorithm. It is measured as the delay achieved in the starting time for soft loads with the scheduling algorithm. A fair algorithm would assign the same long-term average delay to all users.

In [97], the authors propose an autonomous demand response program that guarantees both optimality and fairness. They consider a set of users that are willing to participate in the demand response program as well as the ones that do not take part in this process. They first propose a centralized optimization, then solve the same problem in a decentralized way. To achieve fairness between users, the authors mention the concept of Shapley value, where the impact of each user on the system is calculated by comparing the energy cost attained with and without this user. However, they do not use this concept and propose a billing scheme where each consumer is charged a ratio of the total system bill, which is the ratio of its consumed energy to the total system energy.

The authors in [98] propose a demand response program that considers both fixed and time variant loads. They have incorporated fairness by providing attractive packages to

consumers, which results in reducing peak demands. A fairness index is used and defined as the ratio of satisfied customers (whose demands are fulfilled) to the total number of customers.

Other works have considered fairness within demand management but from a different perspective. For instance, in [99], a mechanism that assigns power to EVs in a fair manner is proposed. This work guarantees a fair access to EVs while ensuring that the distribution network is not overloaded. Similarly, in [100], the authors propose both priority based and round robin scheduling algorithms to maintain fairness within the system.

In [101], a new demand response scheme is proposed, where the need to forecast demand and predict the price elasticity is eliminated. Each consumer submits a set of candidate load profiles for the next day, arranged in the order of preference. Then, a central aggregator will choose the set of optimal load profiles for all consumers, which minimize the cost and maximize the users' utility. This demand response scheme incorporates a fair billing mechanism that consists of penalizing all types of deviations from the total load in real time then readjusting the achieved benefits among participants.

Similarly, in [102], a real time pricing for demand response based on online convex optimization is proposed. The main focus of this paper is on real time pricing with the possibility of price adjustments before the actual scheduling of demands. This is done so that the algorithm can accommodate the variations in consumer behaviors. To ensure fairness between the users while adjusting the prices, a penalty term is introduced for large deviation.

In [103], the authors propose a fair compensation scheme modeled as a game, where the payment system is based on the Shapley value. The main focus of this paper is on cooperative games, where a group of consumers work with each other to achieve the goal of the demand response program. A Load Serving Entity (LSE) is a third party operator, which is used to administer and coordinate the participating consumers. The LSE also puts binding agreements before the start of the cooperative game and fairly distributes the total achieved payoff between all the participating consumers based on the contribution of each one. To be able to attain a fair distribution, the authors propose

the use of the Shapley value. However, calculating this value is computationally complex, they propose an estimation to the Shapley value using a reinforcement learning algorithm that approximates optimal stratified sampling. The authors study different techniques for sampling and approximating the Shapley value. Then, they use these techniques within a demand response program to compensate users by splitting the generated revenue in a fair manner. As opposed to our work, the authors split the revenue generated from coordinating their energy usage in order to reduce the energy cost. The goal is to reward users that reduce their load as a result of enrolling in the demand response program.

2.5 Energy Trading in the Smart Grid

Multiple energy trading mechanisms have been developed due to the advances in information and communications technology. Particularly, the smart grid allows the two-way flow of information and power between all components of the electric grid. In addition, on site reliable electric power is generated by active and well informed consumers as they are equipped with new sources of energy such as photovoltaic panels, fuel cells, and wind turbines. The majority of these customers are also equipped with EVs and other storage units. Energy can be generated at the level of one consumer and transferred to another consumer or even to the main electric grid or an aggregator.

In general, current works on energy trading can be grouped into various categories based on the type of solution used, the involved parties, as well as the different objectives and constraints considered in the trading process.

2.5.1 Trading with a Central Unit

Some works have addressed trading energy with a central unit such as the main grid. In [104], the authors study the feasibility of applying differential pricing schemes to balance the inconvenience that is experienced by an energy user while trading energy with an energy controller in the smart grid.

In [105], a consumer to grid energy management scheme is proposed, where consumers are incentivized to sell their surplus of energy to a central power station. This scheme encourages consumers to take a part in the energy trading by maximizing their social welfare in situations of energy deficiency. A discriminate pricing strategy is used, in which the unit selling price is adjusted according to the number participating consumers and the amount of offered energy for sale. To model the interaction between consumers and the central power station and solve the problem in a distributed manner, a single leader multiple follower Stackelberg game is proposed. The central power station is considered as the leader of the game who is aiming to minimize the total cost achieved from buying energy; whereas consumers are the followers of the game that choose the amount of energy to be sold, which maximizes their utilities.

The main focus of [106] is on the optimal scheduling of different delay tolerant appliances and the optimal use of local energy resources to minimize the energy bill. On the other hand, the authors also study how allowing users to sell energy back to the grid affects the overall energy price. Unfortunately, they do not propose or discuss the specifics of energy trading but rather focus only on optimal task scheduling.

In [107], a multiagent system based approach is proposed to model a dynamic smart grid environment, where homes are considered as agents. In this approach, each home agent takes autonomous decisions to buy electricity from the grid, sell electricity to the grid, charge or discharge batteries, and ignore low priority loads in order to minimize its cost of electricity; while the grid flattens the aggregate demand. In particular, the decisions are prioritized based on the provided utilities, i.e. selling utility, storing utility, and load utility. These utilities are determined using the observations of current and predicted future conditions of the environment. Random models are used to model both the actual diversity and short term prediction of loads, wind generation, and battery storage.

The authors in [108] propose two novel negotiation agents. The first negotiation agent is based on adaptive attitude bidding strategy for energy trading between smart buildings and the utility grid. The negotiation model considers a set of aspects for the integrated smart building and utility grid system. The negotiation agent is able to dynamically

adjust its behavior based on the varying attitudes in the negotiation process. Moreover, the authors propose an improved adaptive attitude bidding negotiation agent based on particle swarm optimization to adaptively adjust the trader's decisions according to the opponent's behaviors.

In [109] a different approach is proposed, where energy is traded between residential users, equipped with distributed energy resources and an energy controller instead of the main grid. A noncooperative Stackelberg game is used to model the interaction between the controller and the residential users and solve the energy trading problem in a decentralized way. The energy controller minimizes the cost of buying energy while the residential users maximize their profits by selling energy to the controller at a lower price instead of the grid.

The authors in [110] investigate optimal management of local energy trading in the future smart grid using pricing. A two layered optimization framework is proposed to study how both the energy users and local trading center can increase their benefits via trading decisions. This work has been extended in [111], where the authors investigate a hybrid energy trading market composed of the utility company and a local market where energy trading is managed by a local trading center. The goal is to benefit sellers and buyers by controlling their energy scheduling and exchange in response to price changes introduced by the local trading center. The authors propose two different types of the local trading center, non-profit-based where it aims to maximize sellers and buyers benefit from local trading, and profit-based where it also maximizes its own profit. The optimal trading price and energy scheduling for buyers and sellers are then calculated for each local trading center type.

In the same context of trading energy with the main grid, other approaches have focused on Vehicle to Grid (V2G) technology. V2G is a concept that was proposed to increase the adoption rate of EVs. Unidirectional V2G requires very little changes to the existing infrastructure, namely the addition of a communication medium between the EVs and an aggregator which combines electricity from a fleet of EVs to flow back to the grid.

In this context, the authors in [112] propose an algorithm for unidirectional regulation

to be used by an aggregator. Different charging algorithms are studied to set the point at which the charging rate varies while performing regulation. An algorithm for maximizing the aggregator profit is then formulated alongside optional constraints for price and system load. Finally, the authors validate the optimal algorithms through simulating a hypothetical group of 10000 EVs in the Pacific Northwest. Results illustrate that using the optimal algorithm increases the aggregator's profits, minimizes the customer costs and reduces system load impacts.

Another approach is proposed in [113] where the coordination of unidirectional V2G services with energy trading is studied. The objective is to maximize the V2G aggregator profit while maintaining the risks associated with energy trading at acceptable levels. This problem is formulated as a mixed integer stochastic linear program while taking into consideration the uncertainties in energy prices, wind availability, and load.

In [114], an energy scheduling problem in a power system where energy trading is permitted is proposed. The trading is between an aggregator and customers equipped with electrical vehicles. Both a collaborative and a non-collaborative approach are proposed. In the collaborative approach, an optimal distributed load scheduling algorithm is used to maximize the social welfare of the power system. A non-cooperative game is used to model the non-collaborative approach, where players are selfish customers trying to maximize their profit by load scheduling and trading energy.

In [115], the authors propose the use of a mixed-integer linear programming framework to model a HEM structure. The HEM system incorporates a distributed small-scale renewable energy generation system, the Vehicle-to-Home (V2H) and V2G capabilities of an EV in conjunction with two-way energy trading of Energy Storage System (ESS), and different demand response strategies. The authors examine the impacts of EV owners preferences, the availability of ESS and the energy trading capabilities on the reduction of total electricity prices.

2.5.2 Trading between Microgrids

Other schemes have focused on trading energy between multiple microgrids that operate in island mode. They are mainly trying to satisfy their local demands without the need of the main electric grid. Trading can be also used to manage the non-dispatchable distributed energy resources within the microgrids.

For instance, in [116] the energy trading problem between microgrids is explored where the surplus generated by renewable energy sources can be traded with other microgrids to reduce the reliability of the grid. A double auction mechanism is proposed to for the energy trading problem.

In [117], the authors propose an optimal energy management framework to model the operation of connected microgrids where energy is exchanged between them in order to utilize the fluctuations of stochastic energy sources and demands. A multi-objective function is used in the optimization to minimize the total cost, which takes in to consideration the operating cost of distributed generators, power exchange with the main grid, the payment for demand response load, penalty costs of involuntary load curtailment, and renewable energy spillage.

An approach that uses a central controller of microgrids is proposed in [118]. This microgrid controller is used to fully control the local distributed energy resources as well as the load to optimize the production of these resources and the energy exchange with the main grid. Multiple market policies are considered, where for instance the controller can serve the total demand of the microgrid without involving the main electric grid. On another market policy, the microgrids take part in the energy market, here the controller maximizes the profit of the aggregator while exchanging energy with the grid.

In [119], multiagent systems are used to simulate multiple microgrid market scenarios. A two-level architecture is used, which is composed of multiple agents such as load agents, generation agents, auction agents, and storage agents. These agents can be either field level agents or market level agents. The field level agents are in charge of balancing local load and generation. The agents that act at the market level are responsible for energy management between multiple microgrids.

The authors in [120] use bi-level programming to study the effect of both the price levels and demand fluctuations on the production and load curtailment. At the upper level, central production units, they minimized the production cost; while at lower level, energy service providers, they minimized the net profit by taking into consideration multiple decision constraints such as load curtailment, profit, and retail price.

A convex optimization framework is proposed in [121] for energy trading between islanded microgrids in order to minimize the global system cost. A distributed iterative algorithm is also proposed where each microgrid solves a local optimization problem to determine the amount and the price of energy to be traded with its neighbors. This iterative process keep executing and the prices keep changing until the demand matches the supply, namely clearing the market.

A fully distributed mechanism for energy trading between microgrids is proposed in [122]. The competitive sellers first decide the amount of energy to be sold in order to maximize their revenue while the buyers follow the sellers by selecting their price bids. A multi-leader multi-follower Stackelberg game is used to analyze this hierarchical non-cooperative energy trading problem. A similar approach using a multi-leader multi-follower Stackelberg game is proposed in [123], where each PHEV acts as a leader that determines the amount of energy to request from the selected microgrid, which act as followers and determine the price per energy unit to sell.

Another type of game is used in [124] to model energy trading among microgrids, which can act as either sellers or buyers that are also connected to a power plant as a backup energy supply. The prospect theory-based static game used in this approach takes into consideration the subjective view of the microgrids, which is ignored by the conventional game theory.

2.5.3 Trading between Users

Other works focus on directly trading energy among users of the smart grid without the involvement of a third-party such as the grid or an aggregator.

In [125], the authors investigate the effect of introducing the concept of energy trading between neighbors on electricity pricing and demand response programs. They propose a scenario where neighbors are allowed to trade energy and draw conclusions about the grid electricity price decrease due to the shift of demand from the grid to neighboring consumers, and from peak to non-peak hours.

The authors in [126] investigate the impact of grouping individual demand's forecast on load forecasting accuracy, and the effects forecasting errors have on trading in an intra-day local electricity. The impact of grouping on forecasting accuracy was performed by randomly creating groups of different sizes from smart meter data and measuring the resulting accuracy with the mean absolute percentage error. They did not discuss how energy trading is achieved but rather focused on how the grouping affected the trading amount and price of end users.

Within demand response context, a local energy management system is proposed in [127] to manage a cluster of price responsive demands. Particularly, it controls the actions taken by these demands such as buying, selling, and storing energy. The proposed algorithm is based on linear programming, with the objective of maximizing the utility for the cluster of demands while considering the load requirements such as minimum daily energy consumption, energy storage limits, and power availability from DER and main grid. The authors show that there exists a mechanism for profit-sharing, which stabilizes the game.

In [128], the authors emphasize on the market aspects of energy trading between users at a neighborhood level. The design and implementation of an energy market place is proposed where the introduction of variable demand supply driven grid electricity prices is discussed. Various orders of configuration are also used in this market place system in order to acquire specific energy requirements and usage patterns. Before accepting an order from a market participant; it has to go through the communication manager that performs the initial security checks. Then, another check is done at the verification module, where market rules such as order configuration and price limitations are verified. If the order complies with all the market rules, it will be forwarded to the market kernel module and

favorable response is send to the participant.

In [129], the authors analyze the cooperation between small scale electricity suppliers and end users in direct energy trading using coalitional game theory. They illustrate that it advantageous for both the energy users and electricity suppliers to participate in the coalition since their total revenue increases. The authors also confirm that the revenues are distributed in a fair manner between energy suppliers and end users using an electricity pricing scheme with asymptotic Shapley value.

The authors in [130] study the interactions and energy trading decisions of distributed energy storage units using a game theoretic based framework. A non-cooperative game is formulated between a set of energy storage units in order to trade their energy. Each energy storage unit owner decides on the maximum amount of energy to trade in order to maximize a utility that models the trade off between the revenues and costs of energy trading. A double auction mechanism is used to determine the trading price that controls the energy trading market. The authors show that this mechanism is strategy proof, in a way that every buyer and seller has no incentive in lying in its reservation bids or prices.

In [131], a risk based auction with an adaptive bidding energy trading strategy is proposed, which maximizes the profit based on risk and competitive equilibrium price prediction. The use of available DERs is managed by the auctioneer which receives bids from buyers and asks from sellers. A hybrid immune system based on particle swarm optimization is used for the minimization of fuel cost of generation while taking into account realistic market prices, distributed generator bids, and load bids.

The authors in [132] propose an iterative double auction mechanism for energy trading between selling and buying agents. A central controller acts as an auctioneer that facilitates trading between participating agents. A distributed algorithm executed by the controller aims to maximize the individual utilities of the participating agents and their social welfare.

Another auction based energy trading algorithms that focuses mainly on the security aspect is proposed in [133]. An efficient searchable encryption scheme for auction is presented where a public key encryption is used with a keyword search technique to allow the energy sellers to get desirable bids while preserving the privacy of the buyers.

2.6 Summary and Discussion

In this chapter a general overview of the state of the art was presented. This chapter first discussed different demand response schemes that manage residential loads in general and specifically the load put by the integration of electric vehicles into the electric grid. Various classifications of the demand response programs have existed in the literature. The classification related to this work is based on the way these schemes operate. Centralized and decentralized are the two categories in this classification.

First, in the centralized approaches, in most cases, one central optimizer is used to schedule the energy usage of each individual appliance. In addition, it is responsible for gathering all the needed information in a given area or house in order to reach a specific objective such as minimizing the cost, minimizing the power losses, and maximizing social welfare. In general, the centralized schemes can guarantee optimum solutions given that all the required information is available. However, these optimization techniques are very difficult to solve analytically due to the substantial amount of data about each individual device and the different system constraints used such as the system capacity and the generated load of the customers.

In the decentralized approaches, agents can communicate and share an amount of information so that each agent will locally find an energy schedule. Each device will make autonomous decisions about their energy usage. For an instance, an iterative procedure can be used, where each device will locally solve an optimization problem and share his information with either a central entity or the other devices and adjust the energy schedule until a global optimal solution is found. These approaches are able to offer a solution that can map to a distributed environment; however, the inherent challenge in these approaches lies in the fact of controlling the growing energy consumption schedule for a group of devices.

Another category of residential load management, which can be either centralized or decentralized, that takes into consideration the users' comfort. These approaches have not only addressed the same objectives of load management such as minimizing the energy bill of each user or the system cost but also the users' needs, which lie in the way they prefer

their energy appliances to be scheduled.

Within the same concept of demand management, this chapter also presented various billing schemes that are used in the literature. Focusing mainly on the issue of fairness and how it is addressed by different approaches. For some mechanisms, a fair demand response would assign the same delay while scheduling appliances to all customers. Others have defined fairness from a different perspective, where the price paid by each user is associated with the type of appliance and its priority compared to other load and his income. Others have adopted the concept of penalizing users that deviate from the calculated schedules as a way to incorporate fair billing.

Another way to manage residential load in the smart grid is achieved by finding economical and clean energy resources through the process of energy trading. An overview of the state of the art of energy trading schemes were addressed next in this chapter. According to the reviewed material in this chapter, energy trading approaches are grouped into several categories depending on the involved participants. Some works focused on trading with one central unit such as the main grid or an energy aggregator. While others have considered trading between multiple microgrids, where both meeting the local loads as well as making profit are considered in trading process. Finally, other schemes have emphasized on trading between individual users, which are equipped with energy storage units and DERs.

In the following chapters more concise review related to the work addressed in this thesis is presented. We will discuss the major contributions in the fields of load management and energy trading within the smart grid.

Chapter 3

User-Aware Game Theoretic

Approach for Demand Management

Demand management programs intend to maintain supply-demand balance and reduce the total energy cost. In this chapter, we propose a user-aware demand management approach that manages residential loads while taking into consideration user preferences. Maximizing users' savings and comfort can be two contradicting objectives. We identify a trade-off between these two objectives and propose an energy consumption optimization model as well as a game theoretic approach to take this trade-off into account. User comfort is modeled in a simple way that considers waiting time, type of appliance, as well as a weight factor to prioritize comfort over savings. The proposed game is based on a modified regret matching procedure and borrows advantages of both centralized and decentralized schemes. Through simulations, we show that the proposed approach is scalable, converges in acceptable times, introduces a very limited amount of overhead in the system, achieves very high cost savings and preserves users' preferences. Extensive simulations are used to evaluate the performance of the optimization model and the proposed approach.

3.1 Introduction

In this chapter the two-way communication link between the users and the utility company is assumed to be reliable, with negligible delay, low error rate, and high bandwidth. This can be achieved under today's technologies such as Fiber-Wireless (Fi-Wi) [134] or high speed LANs. Within the same house, appliances can communicate with the smart meter using Wi-Fi.

Recently, climate change, scarcity of natural sources, as well as increased energy dependency on fossil fuels all have resulted in a global evolution on how energy is generated and consumed. At the same time, energy demands are expected to increase significantly in the next decades; as stated in [1], by 2020 the consumption rate will increase by 75% compared to 2000. As a result, utility companies were forced to rethink their electricity generation and delivery from the bottom up in order to face unprecedented challenges. With the innovation in information and technology, smart grid is a new concept that has been proposed to update and transform the current electrical grid. According to [135], it will introduce distributed renewable sources, diminish the effects on climate change by widespread adoption of electrical vehicles, reduce energy consumption, and meet the current and future customers' requirements.

With the emergence of the smart grid, demand management is a significant component that enables utility companies to match demands to the available energy supply. According to [24], demand response can be defined as the set of mechanisms used by utility companies in order to manage end-user energy consumption in response to supply conditions. Different strategies are introduced to motivate consumers to take part of the process such as encouraging them to change their energy consumption based on changes in electricity prices.

In general, demand response mechanisms work by either shifting or reducing the energy consumption. Reducing the energy consumption is achieved by pushing consumers to adopt energy-aware patterns [136]. Shifting, on the other hand, is achieved by encouraging consumers to shift the operation of their appliances to a later time in order to avoid creating peaks. The act of shifting energy usage may not be compatible with all users' needs. In fact,

shifting may increase users' savings but may also degrade their comfort. This clearly shows that achieving high savings and comfort at the same time can be contradicting objectives. Therefore, there is a need for a mechanism that takes into consideration the different users' requirements. Such mechanism must also take into account existing heterogeneous types of appliances, and provide the users with a straightforward way to choose comfort over savings, or achieve a balance between them. Besides considering users' needs, it should also provide utility companies with high incentives to push them to collaborate, such as cost savings, flattening the load, and removing rebound peaks. It also has to incorporate advantage of existing centralized and decentralized schemes. Driven by these challenges, we propose a game theoretic approach where each player executes a modified regret matching procedure [137] to select the best energy consumption schedule to reach the aforementioned objectives. The proposed game adopts advantages of both centralized and decentralized schemes as we discuss in the next section. In fact, users make their own energy planning decisions locally, which does not require extensive computation capabilities. They are also not required to directly interact among each other's, which saves communication bandwidth and avoids sharing details about their consumption schedules with each other's.

Previous works on demand management can be classified into three major categories: centralized, decentralized, and comfort-based.

In the centralized approaches, a central entity calculates the optimal energy consumption schedule. For instance, in [30], a decision support tool is utilized to schedule appliances using various time-of-use prices. In [27], an optimization-based model is proposed to calculate the optimal day-ahead appliance scheduling under hourly pricing and peak power-limiting based demand response strategies. Similarly, in [28], convex programming model is used to formulate an optimal control of electricity consumption in order to minimize electricity payment and waiting time under real time pricing. In [46], a dynamic scheduling system is used to schedule energy consumption based on predicting appliances' operation using historical data. The authors in [42] propose the use of a third party that manages the load of a group of customers by formulating load scheduling as a constrained multi-objective optimization problem. There is a large body of centralized optimization-

based schemes in the literature. Each has a different goal and uses a different optimization technique to calculate the optimal solution. For instance, [37] uses particle swarm optimization, [43] uses a heuristic approach, [40] and [83] use stochastic and robust optimization techniques, while [41] has opted for mixed-integer programming. In general, centralized approaches can guarantee the optimal solution. However, they are computationally expensive and might not scale well. They also suffer from a single point of failure and require global information from all entities within the system.

Decentralized approaches provide a solution which maps into a distributed environment in a natural way. Optimization is done locally to reach system wide objectives by exchanging information between involved agents. For instance, the authors in [47] propose a game to balance the load and reduce the peak to average consumption ratio (PAR) in a neighborhood. All users within this game contribute to finding the optimal consumption schedule by solving a local optimization problem and sharing the results with other users. A similar approach is used in [48] and [55]. A Stackelberg game is proposed in [50]. The goal is to reduce energy generation costs and consumers' electricity bill. The game is played by different utility companies and end-users, each strives to achieve the maximum profit and payoff. Similarly, Stackelberg is also used in [51] and [53]. In [53], the authors presents game-theoretic frameworks for demand response at both electricity market and consumer levels, where a Stackelberg game is used to model the interaction between a demand response aggregator and electricity generators. Then, the aggregator interact with consumers in order to minimize the inconvenience of consumers while reducing the total load to the intended level. In [57], a class of non-cooperative games (congestion game) is used to control demands using dynamic pricing. The authors in [58] formulate a cooperative demand response scheme for load management as a constrained optimization problem that generates Pareto-optimal response strategy consumer profiles. In [64], a different approach based on decomposing the overall demand response optimization problem into individual subproblems solved in a decentralized way by the use of coordination signals is proposed. Similar approach is used in [66] and [67]. A three-step approach is proposed in [68] for managing a fleet of EVs. It combines both centralized and decentralized methods for scheduling the EV charging based on demand and supply functions.

Table 3.1: Comparison of Demand Management Approaches

	Centralized	Decentralized	Our approach
Energy Planning	Central	Local	Local
Solution Methodology	Optimization	Game Based on Local Optimization	Game Based on Modified Regret
Energy Demand Sharing	With Trusted Central Entity	With Neighbors	With Trusted Central Entity
Inter-Agent Communication	No	Yes	No
Central Entity Required	Required for Solving Optimization	Not Required	Required for Cost Calculation

The last category of demand response programs takes users' well being into consideration while attaining the same energy and cost minimization objectives. Some papers have used the concept of household loads priorities where highest priority energy requests are met first. These include [25], [70], [78], and [80]. Other works such as [73] require the users to manually specify a set of preferences that determine the rank and the schedule of each appliance, in the form of a preference matrix. The authors in [72] model different user's requirements using a willingness to pay parameter (wtp). However, the wtp parameter is used as a way to affect the price rather than the comfort. The authors in [86] propose another approach based on dual decomposition that aims to maximize the social welfare. This is achieved by minimizing the total cost of both end users and utility company, and the total dissatisfaction of the end users. User's satisfaction is modeled using a disutility function that maps the amount of power used to a satisfaction level, which decreases as the amount of power deviates from a desired level. Similarly [87] proposes a sigmoid function that models the comfort in terms of the amount of power used by an appliance. In [71], a peak-to-average ratio constrained energy scheduling approach for household appliances

is proposed, which minimizes the inconvenience of customers due to the shifting of their appliance schedules. Another approach proposed in [88] requires the user to specify their tolerance to changing the appliance use time; however, the only purpose is to minimize the energy cost without taking into account the effect of this tolerance on the user's comfort. The authors in [89] model the user comfort by considering thermostatically controlled appliances only, where each user needs to provide the preferred temperature and the maximum acceptable deviation.

The closest work to ours that studies the trade-off between the user's comfort and electricity payment is [92]. The authors propose an optimization problem to minimize the waiting time or the electricity cost by adjusting a knob parameter in the objective function. However, choosing a value for this parameter is not intuitive for the user, as the range proposed by the authors is imprecise. It also does not give a clear idea on the achieved trade-off. The authors in [92] model the comfort as a waiting time associated with a cost. According to this model, the cost of waiting increases as more energy is consumed in later hours. Therefore, if an appliance consumes a high amount of energy in the first hours and a very low amount of energy in a later hour, its cost of waiting would be smaller than the case where it consumes all of its energy in the last hours. However, from a user's perspective, both situations are the same since in both cases the appliance is delayed and would not be ready until the same (late) hour. Therefore, this model may fail to meet users' expectations. Finally, the authors in [92] do not study how the system responds in the presence of different types of appliances.

The proposed demand management algorithm is based on a game theoretic approach, which is not fully centralized, neither fully decentralized. Every player in the game performs its own calculations and makes its decisions locally. However, these actions are based on a public signal that is calculated by a central entity (Table 3.1). More specifically, players send their energy consumption schedules to the utility company that will calculate the energy cost and send it back to them. The users will not reveal any information about their energy usage to other users, which motivates them to participate in the game. The proposed game adds flexibility in a way that gives the consumers the choice to prioritize

either comfort, savings, or achieve a balance between them. Unlike [92], we propose a simple weight factor that ranges from 0 to 1 to capture the trade-off between cost savings and user comfort. We also model the comfort as a waiting time, which is based on the actual delay achieved by considering the time when the appliance becomes ready. By opting for the modified regret matching procedure as a learning algorithm in games, users can achieve high savings and/or comfort without the need of demanding computational capabilities as is the case for optimization approaches. Finally, even if users do not communicate or directly interact between each other's; the algorithm attains fundamental system performance compared to the optimal solution, as shown in the simulation results.

The contributions of this chapter are as follows:

- First, we propose a model for different types of appliances, and a simple way to model user preferences that is based on waiting time, type of appliance, and a weight factor to prioritize either comfort or savings.
- Second, we propose a centralized optimization model to serve as a benchmark for performance evaluation.
- Third, we propose a game theoretic approach to model the energy consumption problem that allows the users to minimize their energy bill, maximize their comfort, or reach a balance.
- Fourth, we perform extensive simulations to evaluate the performance of the proposed algorithm. We compare its performance against the uncontrolled consumption as well as the optimization model.

The rest of the chapter is organized as follows. The system model is presented in Section 3.2 and formulate the optimization problem in Section 3.3. Section 3.4 discusses the proposed demand management algorithm. Performance evaluation results are shown in Section 3.5 while Section 3.6 concludes the chapter.

3.2 System Model

3.2.1 Power System

We consider a residential neighborhood that consists of multiple users sharing the same energy source such as a generator connected to the electric grid. Each user will have multiple smart appliances of different types. Some of which are able to shift their energy schedules while others have strict schedules. We identify two scenarios, in the first one, each appliance will be able to communicate directly with the energy source (utility company). In the second, appliances will communicate with an energy controller installed within the smart meter of each house. The controller can be as simple as an aggregator, which aggregates the energy schedules of all appliances in the house in order to save communication bandwidth. In this case, less messages are exchanged between the utility company and the customers. It can also act as an energy scheduler that changes the energy schedules on behalf of appliances. Note that the energy controller within each house is not a third-party aggregator as in [138], but is simply a device that aggregates (and controls) energy consumption for appliances in the same house. For simplicity purposes, we will use the first scenario throughout the rest of the chapter. It is true that the first scenario is quite unrealistic; however, extending it to the second scenario requires few simple changes. If the energy controller works as an aggregator only, then nothing changes from the point of view of both appliances and the utility except that all messages go through the controller. If the energy controller works as both an aggregator and a scheduler, then it will be responsible for running the energy scheduling game on behalf of each appliance in the house and send it back its final energy schedule.

3.2.2 Load Management Model

We consider a set of appliances $\mathcal{N} = \{1, 2, 3, \dots, N\}$, where N is the total number of appliances in the system. We also assume that time is divided into equal timeslots h such that $h \in \mathcal{H} = \{1, 2, 3, \dots, H\}$. The timeslot can represent any unit of time, we choose one hour for simplicity purposes. Each appliance $n \in \mathcal{N}$ is considered to have an energy

consumption schedule as follow:

$$x^n = [x_1^n, x_2^n, \dots, x_H^n]. \quad (3.1)$$

where:

$$x_h^n = \begin{cases} 1, & \text{if } n \text{ is using energy at } h. \\ 0, & \text{otherwise.} \end{cases}$$

For simplicity purposes, we assume that each appliance n uses a fixed amount of energy E^n kWh per timeslot throughout its energy schedule. It also requires a number of timeslots denoted by $\mathcal{T}^n = \sum_{h=1}^H x_h^n$. Note that the proposed method can be extended to support a variable amount of energy within each timeslot by simply changing the parameter E^n to represent the amount of energy consumed per timeslot such that $E_h^n = [E_1^n, E_2^n, \dots, E_H^n]$.

Let t_s^n be the timeslot at which appliance n is scheduled to start and t_f^n when it is scheduled to finish. We assume that both t_s^n and t_f^n are known and that $t_s^n < t_f^n$.

To refrain consumers from using electricity at peak hours, we use a per timeslot cost function $C_h(L_h)$ that is proportional to the total energy usage during the same timeslot h denoted by L_h such that $L_h = \sum_{n=1}^N x_h^n E^n$. Note that $C_h(L_h)$ represents energy cost in terms of cents per kWh in timeslot h . We assume that the cost function is an increasing function such that for every $h \in \mathcal{H}$ $C_h(L_h^1) < C_h(L_h^2), \forall L_h^1 < L_h^2$. The cost function is assumed to be strictly convex. We adopt the same function used in the thermal generation since it is a practical cost function that satisfy previous assumptions [139]:

$$C_h(L_h) = a_h L_h^2 + b_h L_h + c_h. \quad (3.2)$$

where $a_h > 0$, b_h and $c_h \geq 0$ at each $h \in \mathcal{H}$. We consider $b_h = 0, c_h = 0$ for simplicity purposes and a_h is the hourly wholesale price of electricity. It is worth noting that this cost function can either represent the actual energy cost as the case of thermal generators or merely artificial cost tariffs used by the utility to enforce load control [47]. In our case, we use it to generate artificial cost tariffs that depend on the load per timeslot in order to impose a proper demand management.

3.2.3 Modeling of the Comfort

Each appliance n within the house consumes energy in a different manner based on its type T^n and requirements. We consider three types of appliances:

- Hard ($T^n = 1$): Appliances that are non-shiftable; they stick to their original energy consumption schedule. Examples include fridges and lights.
- Soft: Appliances that can shift their original energy consumption schedule according to specific constraints. We have two types as follows:
 - Consecutive ($T^n = 2$): Appliances that run in a cycle such as washers and dryers. They can not be interrupted once started and must keep running till the end of their cycle.
 - Non-Consecutive ($T^n = 3$): Appliances that can be interrupted while running, they can run in non-consecutive timeslots. A perfect example of this category is the electric vehicle battery.

To model user preferences per a given appliance, we introduce a parameter called Δt_{max}^n to specify the maximum delay tolerated by the user for appliance n such that $\Delta t_{max}^n \geq 0$. For instance, a user could specify the latest deadline when he is expecting his electric vehicle n to be ready as the timeslot t^n by choosing $\Delta t_{max}^n = t^n - t_f^n$. Then the proposed load management algorithm will choose the best charging slots between the original charging time t_s^n and $t_f^n + \Delta t_{max}^n$ so that the user bill is reduced and the load is minimized taking into account the user preference. Note that Hard appliances ($T^n = 1$) have Δt_{max}^n set to zero. Therefore, Δt_{max}^n , the maximum delay associated with appliance n is used to control the user's comfort.

When the proposed load management algorithm decides to shift an appliance to finish running at a later time $t_f^n + \Delta t^n$, Δt^n represents the delay associated with the shifted schedule. Note that $\Delta t^n \leq \Delta t_{max}^n$ and is calculated as follows: $\Delta t^n = \max_{h=1}^H (h \times x_h^n) - t_f^n$.

As Δt^n increases, the user's comfort decreases. The actual discomfort associated with an energy consumption schedule is defined as follows:

$$D^n = \frac{\Delta t^n}{\Delta t_{max}^n} \quad (3.3)$$

The worst discomfort happens if the actual delay Δt^n is the same as Δt_{max}^n .

3.3 Problem Formulation

In this section, we formulate an optimization problem that minimizes the total system bill while preserving the user comfort. The purpose of this model is to shift the energy consumption schedules within the residential neighborhood in order to achieve optimal savings. The purpose is not to reduce the amount of consumed energy but to find the optimal energy schedules for each appliance that would reduce the bill and maximize comfort.

Users specify the initial energy consumption schedules x^n for each appliance n . Using the expressions in (3.1) and (3.2), we can define the energy bill in terms of the energy consumption schedules as follows:

$$B^n = \sum_{h=1}^H x_h^n E^n C_h(L_h) \quad (3.4)$$

The energy bill is a function of the amount of energy consumed, the cost per timeslot, and whether the appliance is consuming energy at this hour or not.

A cost effective energy consumption scheduling can be expressed in terms of minimizing the energy bill of all appliances in the system, as the optimization problem below:

$$\underset{\forall n \in \mathcal{N}}{\text{minimize}} \sum_{n=1}^N B^n \quad (3.5a)$$

subj. to

$$x_h^n = \{0, 1\}, \forall h \in \mathcal{H}, \forall n \in \mathcal{N} \quad (3.5b)$$

$$\sum_{n=1}^N x_h^n = \mathcal{T}^n, \forall h \in \mathcal{H} \quad (3.5c)$$

$$x_h^n = 0, \forall n \in \mathcal{N}, \forall h \in \mathcal{H} \mid h < t_s^n \quad (3.5d)$$

$$x_h^n = 0, \forall n \in \mathcal{N}, \forall h \in \mathcal{H} \mid h > t_f^n + \Delta t_{max}^n \quad (3.5e)$$

$$\mathcal{T}^n = \max_{h=1}^H (h \times x_h^n) - \min_{h=1; x_h^n \neq 0}^H (h \times x_h^n) \quad (3.5f)$$

$$\forall n \in \mathcal{N} \mid T^n = 2$$

The problem in (3.5a) of finding the optimal energy consumption schedules is modeled as a binary integer programming problem. Constraint (3.5b) ensures that each appliance n is either using or not using energy at timeslot h , where x_h^n is the decision variable of the optimization problem. Constraint (3.5c) ensures that each appliance n uses exactly the required number of timeslots. Constraints (3.5d) and (3.5e) ensure that an appliance is not scheduled before its initial start time t_s^n and does not finish running after the maximum delay tolerated by the user Δt_{max}^n , respectively. Finally, constraint (3.5f) ensures that soft-consecutive appliances use consecutive timeslots where $\max_{h=1}^H (h \times x_h^n)$ and $\min_{h=1}^H (h \times x_h^n)$ represent the last and first charging timeslots under consumption schedule x^n .

The model in (3.5a) does not take the users' comfort into consideration. The users' preferences are specified by setting the type and the maximum accepted delay Δt_{max}^n of each appliance. Therefore, an efficient comfort aware energy consumption scheduling optimization problem can be expressed as follows:

$$\underset{\forall n \in \mathcal{N}}{\text{minimize}} \sum_{n=1}^N \left(w^n B^n + (1 - w^n) D^n \right) \quad (3.6)$$

where w^n is a weighting factor that allows the user to prioritize comfort or cost saving, such that $w^n \in [0, 1]$. For example, if a user of an electric vehicle sets $w^n = 1$, then, he only cares about reducing the charging cost rather than when his vehicle is going to be ready. Still the solution preserves that the maximum delay will not be exceeded. The same constraints (3.5b), (3.5c), (3.5d), (3.5e), and (3.5f) apply to the optimization problem in (3.6).

3.4 Demand Management Algorithm

3.4.1 Energy Consumption Game

We have opted for a game theoretic approach, where both consumers and the utility interact to solve the energy consumption problem and reach overall system savings. Learning constitutes an integral part in game theory. Numerous learning algorithms, which enable players to reach a specific desired outcome, exist in the literature [140]. Examples include best response dynamics, fictitious play, and smooth fictitious play, all based on utility maximization. In general, it is required in such algorithms that a player observes the actions played by all other players and solve an optimization problem at each iteration, which requires high calculation capabilities. Using these algorithms to solve the energy consumption problem implies that each player must share its consumption schedule with all other players, which introduces significant message exchange and violates privacy.

The modified regret matching based procedure proposed in [137] is based on a regret matching learning algorithm. The players need to calculate the regret, which is simply defined as the increase, if any, in the average payoff that would result if all past plays of the current action were replaced by the new action (and everything else remained the same). The purpose of each player is to minimize the regret of selecting a given action j ; therefore, if at a specific period a player chooses action j , then the probability of playing a different action k in the next period will be proportional to the regret for not having played k instead of j in the past.

We have opted for the modified regret matching based procedure in [137] for the following reasons:

- The strategies don't require solving an optimization problem and hence aren't computationally expensive.
- A player only needs to know the payoffs he received in the past to calculate the regret and not other players' payoffs.

- A player does not have to share his actions with other players. He only needs to observe a common public signal to calculate his payoff (total load), which incurs limited message exchange.

Appliances are modeled as players willing to use energy at different timeslots. The proposed game takes advantage of the fact that some shiftable appliances can change their original energy consumption schedule in order to reduce their energy bill. Hence, each shiftable appliance can choose among a number of different schedules, denoted in the game by actions.

Players in the system are denoted by the set \mathcal{N} . Each player $n \in \mathcal{N}$ selects the energy consumption schedule x^n that would maximize his payoff, which not only depends on his action but also on other players' actions. We denote the set of feasible actions for player n as $\mathcal{S}^n = \{1, 2, 3, \dots, S\}$ where S is the total number of actions/schedules. This is calculated by each player before starting the game by including all possible schedules (combinations) that satisfy constraints (3.5b), (3.5c), (3.5d), (3.5e), and (3.5f).

The proposed game is repeatedly played over a number of fixed periods called stages. During each stage t , player n makes a move by choosing a specific consumption schedule s_t^n from the set \mathcal{S}^n . The payoff received by player n at stage t is defined as follows:

$$U_t^n(s_t^n, s_t^{-n}) = - \left[w^n B^n + (1 - w^n) D^n \right] \quad (3.7)$$

where s_t^n represents the actions selected by player n at stage t and s_t^{-n} the actions selected by all other players except n . As more players decide to use energy during the same timeslots, their bill increases which causes the payoff to decrease. In (3.7), B^n represents the bill of player n when selecting action s_t^n . The best case scenario would be that player n is the only one using energy during specific timeslots, hence paying the minimum energy cost. This means that his bill is going to be reduced, which will increase his payoff. The worst case scenario will happen when player n uses energy in timeslots that are used by all other players. This will induce an energy price hike which will increase his bill, and therefore decrease his payoff.

Notice that in order to calculate the payoff, each player needs to know the energy cost $C_h(L_h)$. This value can be easily calculated by the utility company after it receives all the players' energy consumption schedules (actions). In this case we take advantage of the existing smart grid architecture, where such central entity receives the total hourly energy usage for billing purposes. This solution introduces a single point of failure and can be replaced by electing a leader which will take this responsibility. A fully distributed solution can also be adopted where every user sends his hourly energy usage to all other users. This way, every user can perform the needed calculations without the need of a central entity. In this later case, privacy becomes a major concern, which could discourage users from playing the game.

The offered privacy in the proposed algorithm is maintained by not sharing the load schedules with other users but only with the utility company, which is collected for billing purposes anyways. We assume that the utility company is a trusted authority that maintains the confidentiality of customer information and encryption schemes are used to protect transmitted data. In addition, a smart meter can be used to aggregate a user's appliances' total energy usage and send it to the utility company. In this case, users do not reveal the details about the energy consumption of their own appliances. A similar approach was adopted in [47].

At the start of each stage, players send their chosen actions, i.e. consumption schedules, to the utility. Therefore, each player only needs to exchange one message, its schedule, per stage with the utility, while the utility sends back the same message (energy cost per time slot) to all players. This results in a very limited message exchange between the players and the utility. In fact, only $2 \cdot N$ messages have to be exchanged per stage.

3.4.2 Modified Regret-based Algorithm

The proposed algorithm is based on a modified regret matching procedure described in [137] that is carried out by every player. The average regret is calculated by each player after each stage and is used to determine the action to be chosen in the next stage. Player n calculates the regret for not having chosen action k when he chose action j at stage t , such

that $j = s_t^n$, for every $k \neq j$ as:

$$Q_t^n(j, k) = \max\{C_t^n(j, k), 0\} \quad (3.8)$$

where

$$C_t^n(j, k) = \frac{1}{t} \left[\sum_{\tau \leq t: s_\tau^n = k} \frac{p_\tau^n(j)}{p_\tau^n(k)} U_\tau^n - \sum_{\tau \leq t: s_\tau^n = j} U_\tau^n \right] \quad (3.9)$$

Equation (3.8) is an estimation of how much player n regrets at stage t not selecting consumption schedule k instead of j in the past. It basically measures the difference (strictly speaking, its positive part) of the average payoff over the stages when consumption schedule k was selected and the stages when consumption schedule j was selected. In other words, when the user does not regret not choosing action k in the past over j ($C_t^n(j, k) < 0$), the regret is set to 0. $p_\tau^n(j)$ and $p_\tau^n(k)$ represent play probabilities for actions j and k at stage $\tau \leq t$, respectively. If at stage t , player n selects an action j , the probability of choosing action $k \neq j$ in the next stage is approximately proportional to the calculated average regret from j to k and is depicted in (3.10). Action j is chosen again in the next stage with the remaining probability (3.11). This means that action j is chosen again in the next stage $t + 1$ only if $p_{(t+1)}^n(j) > p_{(t+1)}^n(k)$ for all $k \neq j$. Otherwise, a different random action $k \neq j$ is chosen. Therefore, the player will select actions with high regrets in the next stages without the need for solving an optimization problem, and over time, the regrets and the average regret between any two actions will be reduced as proven in [137].

$$p_{(t+1)}^n(k) = \left(1 - \frac{\delta}{t^\gamma}\right) \min \left\{ \frac{1}{\mu} Q_t^n(j, k), \frac{1}{S-1} \right\} + \frac{\delta}{t^\gamma S} \quad (3.10)$$

$$p_{(t+1)}^n(j) = 1 - \sum_{k \in S^n: k \neq j} p_{(t+1)}^n(k) \quad (3.11)$$

Note that initially ($t = 1$) p_1^n are chosen randomly given that $p_1^n \geq \delta/S$. S represents the total number of actions for player n . Other variables are chosen as follows: $0 < \delta < 1, 0 < \gamma < 0.25, \mu > 2M^n(S-1)$ for all n , where M^n is an upper bound on $|U^n(s)|$ for all $s \in S^n$. Proofs and explanation for this choice can be found in [137]. To calculate the play

Algorithm 1 Smart Energy Management Algorithm for Player $n \in \mathcal{N}$

Input: Set of s energy consumption schedules \mathcal{S}^n .**Output:** The sub-optimal schedule s^n for player n .

- 1: randomly select an initial energy consumption schedule s_1^n .
 - 2: Random $p_1^n(j) \geq \frac{\delta}{S}, \forall j \in \mathcal{S}^n; t = 1;$
 - 3: **repeat**
 - 4: send schedule s_t^n to the utility
 - 5: Utility:
 - receive all schedules s_t^n from all players $n \in \mathcal{N}$
 - calculate $C_h(L_h)$ according to (3.2)
 - send $C_h(L_h)$ to all players $n \in \mathcal{N}$
 - 6: receive $C_h(L_h)$ from the utility
 - 7: compute $U_t^n(s_t^n, s_t^{-n})$ using equation (3.7)
 - 8: **for** $\forall k \in \mathcal{S}^n | k \neq j$ **do**
 - 9: compute $Q_t^n(j, k)$ using equations (3.8) and (3.9)
 - 10: compute $p_{t+1}^n(k)$ using equation (3.10)
 - 11: **end for**
 - 12: compute $p_{t+1}^n(j)$ using equation (3.11)
 - 13: **if** $p_{t+1}^n(j) > p_{t+1}^n(k)$ **then**
 - 14: $s_{t+1}^n = s_t^n$ (select the same schedule j again)
 - 15: **else**
 - 16: randomly select a schedule s_{t+1}^n from \mathcal{S}^n such that $s_{t+1}^n \neq s_t^n$
 - 17: **end if**
 - 18: $t++;$
 - 19: **until** no player changes his energy consumption schedule
-

probabilities (3.10), (3.11), and the regret (3.8), a player n needs only to observe his own payoffs $U_1^n, U_2^n, \dots, U_t^n$. In fact, players do not know, and do not have to know, anything about who is playing and what their actions or payoffs are.

As discussed in [137], the game will surely converge to the set of correlated equilibria as $t \rightarrow \infty$. At that point, players will not regret their dynamic choice of actions according to Algorithm 1. Each player will attain an acceptable payoff given other players' alternating choices, which translates into savings in the energy bill while considering users' preferences. This results in a system performance where the total energy cost is minimized and the load is balanced throughout different timeslots. Although the proposed algorithm might not achieve optimal results, it does achieve considerable savings in the absence of interaction between players, as illustrated in the next section.

3.5 Performance Evaluation

3.5.1 Simulation Setting

The performance of the proposed load management algorithm is evaluated using OM-NET++ [141]. First, for the regret based calculation we set $\delta = 0.01$, which is chosen for simplicity and convenience only, to guarantee an upper bound we set $\gamma = 0.24$, and μ has to be sufficiently large number but it is sufficient to set $\mu = 2 * 0.001(m^n - 1)$, more details on these values can be found at [137]. For illustration purposes, we consider that each appliance n consumes a random amount of energy E^n between 1 and 9 kWh and requires a number of slots \mathcal{T}^n between 1 and 5, according to a uniform distribution. As a result, the generated energy consumptions schedules span various types of appliances. In general, energy demands during the day are different from those of the night, as energy needs of users change, therefore we set $H = 12$. Overall, higher energy demands are observed in the evenings as most consumers return from their work; whereas, lower demands occur in the late evenings while most of them are sleeping. The same pattern is observed during the day. Hence, we program a higher percentage of appliances to run within the first $H/2$ timeslots. The maximum delay Δt_{max}^n tolerated by the user for appliance n is selected

randomly between 1 and $H - t_j^n$ according to a uniform distribution to represent various user' preferences. For the cost function (3.2), we consider the wholesale price of electricity $a_h = 0.2$ cents in order to give artificial cost rates for simulation purposes. We simulate multiple scenarios where the number, the percentage of types of appliances, and the weighting factor w^n are varying in order to assess the behavior of the proposed algorithm in different situations.

3.5.2 Simulation Results

We evaluate the proposed algorithm in terms of the following metrics:

- **Load:** represents the energy consumption across the different timeslots. It is used to study how the proposed algorithm balances the overall load across the timeslots compared to uncontrolled and optimal energy consumption. The PAR is a ratio between the maximum load consumed within the day and the total average load.
- **Savings:** represents the average percentage of system bill savings. It is calculated as the percentage difference in the total system cost between uncontrolled charging and both the optimal and the proposed algorithm.
- **Comfort:** represents the average percentage of comfort among all users. It is calculated as the percentage difference between the maximum delay and the actual delay achieved for both the optimal and the proposed algorithm.
- **Equilibrium:** represents the average number of stages it takes the proposed algorithm to stabilize. For uncontrolled energy consumption, there is no notion of equilibrium time as appliances stick to their initial energy consumption schedules. Calculating the optimal solution may require huge processing power and memory as the size of the problem increases, but there is no notion of equilibrium time.
- **Pareto Optimality:** is a measure of efficiency. In a game, the outcome is Pareto optimal if there is no other outcome that makes at least one player better off without

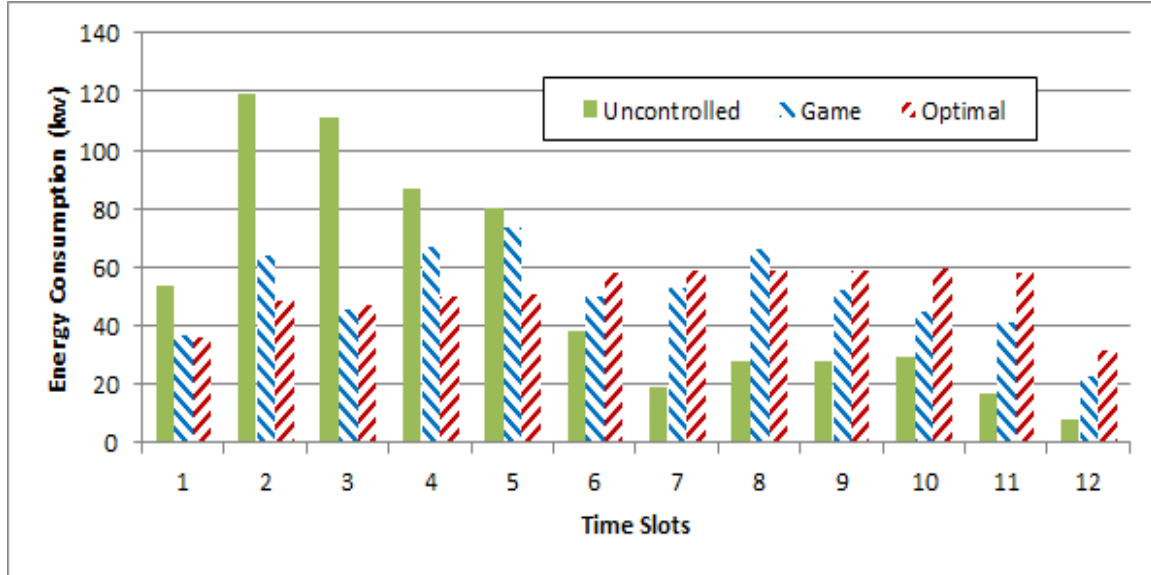


Figure 3.1: Total Hourly Energy Consumption

making another worst off. In our case, the game is Pareto optimal if increasing a user’s payoff decreases another’s payoff.

First, we analyze how the proposed demand management algorithm behaves compared to the optimal centralized solution discussed in section 3.3. Then, another set of simulations is performed in order to explore the scalability and convergence of the proposed algorithm.

In the first scenario, we will set $w^n = 1$ to account for electric bill reduction only. We consider 40 appliances as the optimal solution requires time to be calculated, 30% of these appliances are hard, 35% soft consecutive, and 35% soft non-consecutive. Figure 3.1 shows the total energy consumed within every timeslots. We see that within the uncontrolled algorithm, higher loads occur in the first 6 timeslots, which generates energy peaks. Both the optimization and proposed demand management algorithm are able to remove these energy peaks and balance the load across non-peak hours. The PAR is reduced from 2.31 to 1.16 (a reduction of 49.79%) in the case of the optimal solution and from 2.31 to 1.43 (a reduction of 38.09%) for the proposed algorithm.

In the next set of simulations, every simulation is repeated 30 times and the 98% confidence interval is reported, Appendix C has more details on confidence intervals . To evaluate the effect of appliances’ types on the achieved savings we run an extra set of

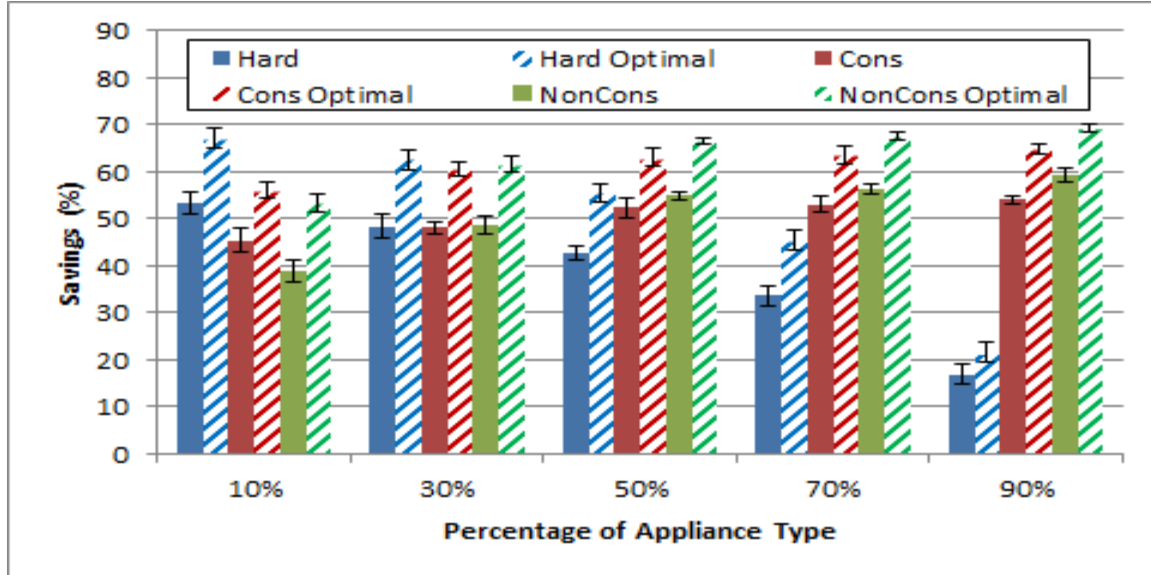


Figure 3.2: Savings Achieved vs. Percentage of Appliances

simulations where we change the percentage of these types. We change the percentage of a given type of appliance and divide the remaining percentage equally between the two other types. For example, when 10% of the appliances are hard, the remaining 90% is divided equally among soft consecutive (45%) and soft non-consecutive (45%). Figure 3.2 illustrates the results. First of all, we see that as the percentage of hard appliances increases, the achieved savings dramatically decrease. In the case of soft-consecutive appliances, the savings slightly increase as their percentage increases. This behavior can be explained by the fact that this type of appliances is not as flexible as the soft-non-consecutive ones. Increasing the percentage of soft-consecutive appliances also means decreasing the percentage of non-consecutive ones. The impact of shiftable loads is clear in the last case of non-consecutive appliances where the best savings are accomplished under a high presence of these appliances. Figure 3.2 also draws the savings calculated using the optimal solution. We see that the average difference between the proposed algorithm and the optimal savings is in the range of 4% (90% hard appliances) and 14% (10% non-consecutive appliances). This means that the proposed algorithm achieves savings that are up to 96% close to optimal savings.

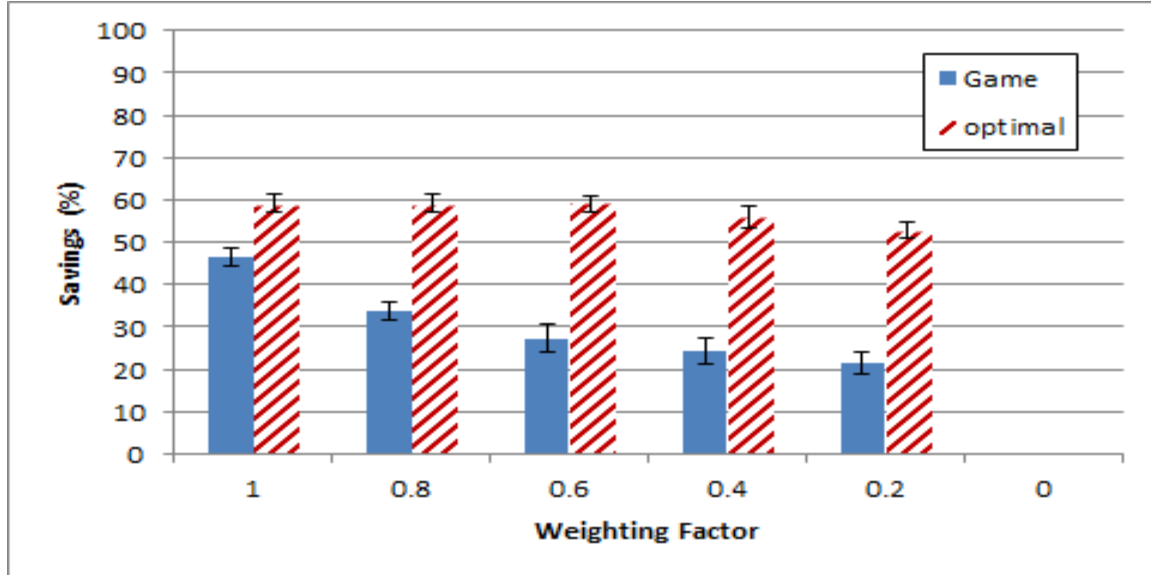


Figure 3.3: Savings Achieved vs. Weight Factor

To study the effect of w^n on both savings and comfort, we run a set of simulations with different values of w^n . The results are illustrated in Figure 3.3 and Figure 3.4. We see that as users give more weight to the comfort, the savings decrease while the comfort increases. The achieved results are also compared to the optimal solution. We notice that in terms of comfort, the proposed algorithm copes very well with the optimal solution, even providing slightly better comfort in most cases. However, we notice that it does not cope very well with the difference in savings. Still, we argue that this is normal as users are not interested in saving but rather in comfort. We see that the proposed algorithm still achieves savings that are 25% close to optimal savings in the worst case ($w = 0.2$).

To show that the game is Pareto optimal, we study the effect a user has on other users when he tries to increase his payoff (by either decreasing his bill or discomfort). If a player decides to reduce his bill by shifting his schedule to a timeslot h with a lower cost, he will cause the energy cost to increase in h , and hence cause the bill of any other user using energy at h to increase (decreasing their payoffs). Similarly, if a player decides to decrease his discomfort by shifting his energy usage to other (earlier) timeslots, he will cause energy cost to increase in those timeslots affecting the bill of users using energy in those timeslots (decreasing their payoffs). Therefore, the game is Pareto optimal and a player cannot

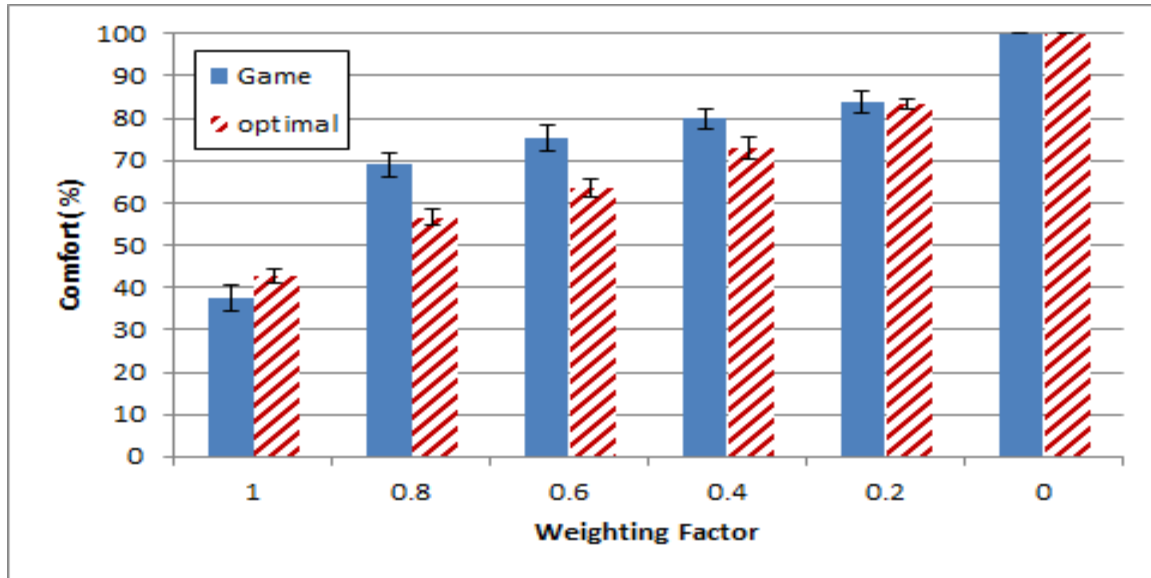


Figure 3.4: Comfort vs. Weight Factor

further improve his bill or discomfort without hurting at least one other player.

In Figure 3.5, the total number of appliances in the system is changed from 20 to 100 with 10 increments to model different neighborhood densities. The rest of the settings were kept the same as previous scenarios. We see that the proposed algorithm achieves very good savings, minimum 40% and maximum 58%. More importantly, the difference between savings of the proposed algorithm and optimal savings fall in the range [9% – 14%].

To study the scalability and convergence of the proposed algorithm, Figure 3.6 shows the savings achieved as the number of appliances is increased from 200 to 1400. The percentage of savings slightly decreases as the number of appliances in the system increases. This can be explained by the fact that as more appliances are introduced into the system, they tend to shift to time slots with lower energy cost, but because of their high number the new energy cost is not significantly reduced. Figure 3.6 shows that the proposed algorithm achieves 23% savings for a neighborhood of 1400 appliances while it achieves almost 40% for a neighborhood of 200 appliances.

The average convergence time, or equilibrium time, is illustrated in Figure 3.7 as a function of the total number of appliances. The equilibrium time represents the number of stages needed for appliances to stick to a final consumption schedule and stop fluctuating

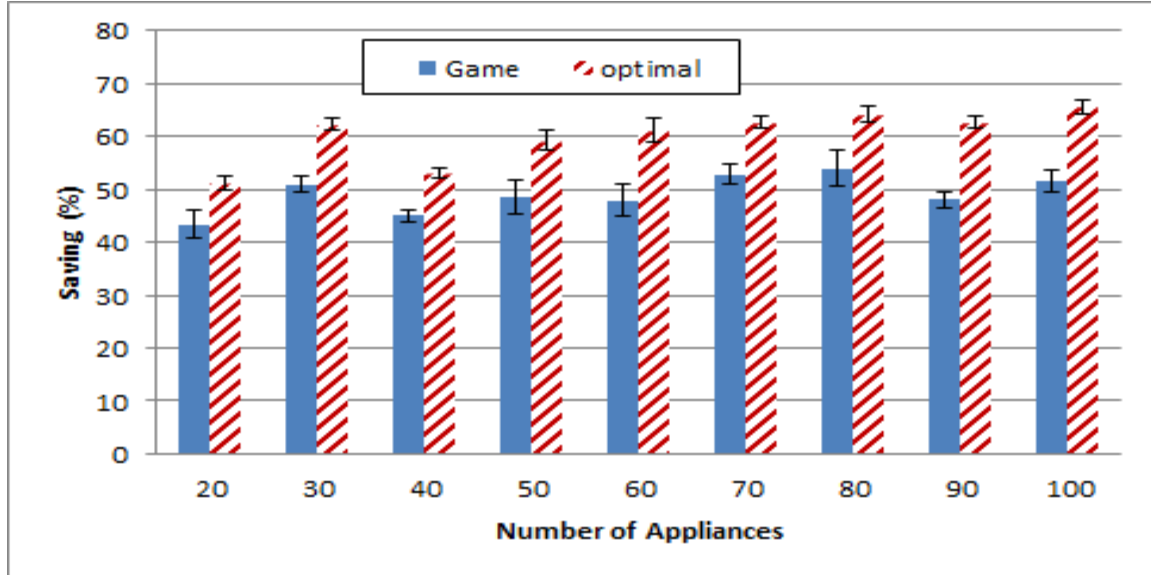


Figure 3.5: Savings vs. Number of Appliances

in future stages. We see that the number of appliances does not affect the equilibrium time, and that it only takes the algorithm 6 stages to converge even for a very high number of appliances.

3.5.3 Discussions

Storage and Computational Complexity

Each appliance calculates the payoff and the regret for not choosing a different energy consumption schedule in the past in order to make a decision in the next stage. The needed information consists of their previous payoffs as well as the set of feasible schedules \mathcal{S}^n . Each appliance then calculates the probabilities for choosing the next schedule. In the worst case, a non-consecutive appliance with $H/2$ maximum delay requirement needs to use energy $H/2$ out of H timeslots. Therefore, an appliance needs to store $S = H!/(H/2)!^2$ feasible schedules. Each schedule requires H binary variables of size 1 bit. This requires $H(H!/(H/2)!^2)$ bits of memory storage. For $H = 12$, this translates to $1.45KB$. Assuming payoff values are 32 bit floats, it only requires $H!/(H/2)!^2$ Bytes of memory storage to keep history of the payoffs. For $H = 12$, that translates to $3.6KB$. In addition, computing

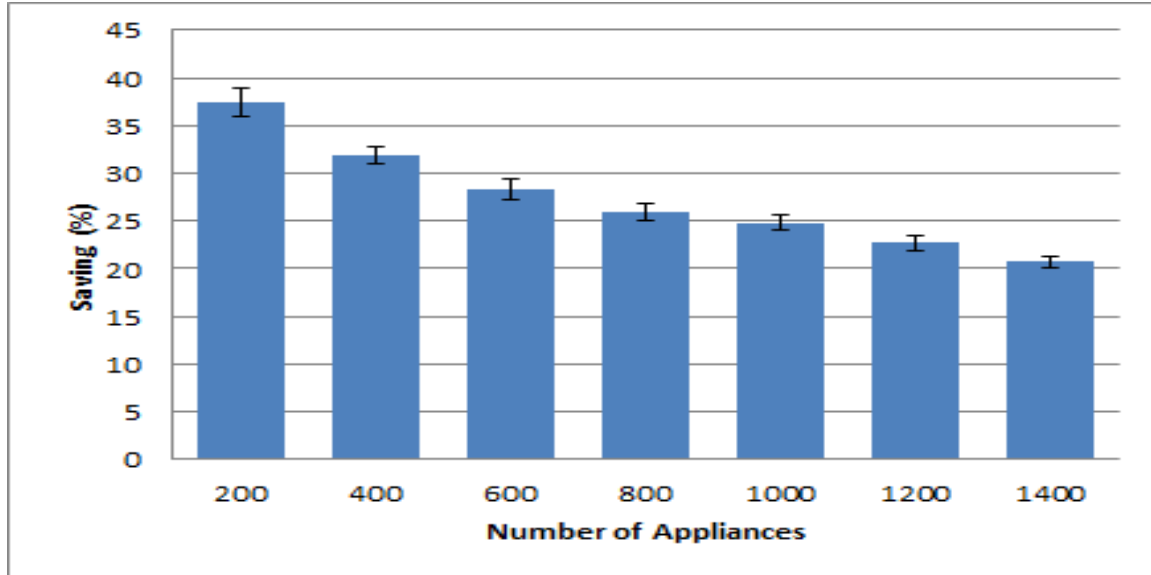


Figure 3.6: Savings Achieved with Load Management Algorithm vs. Number of Appliances

the regret in (3.8) is $O(1)$. Therefore, the proposed algorithm not only converges in a few stages but is also computationally light ($O(S)$) and does not require high memory or processing power.

Synchronization

Obviously, the proposed algorithm requires appliances to support some kind of loose synchronization with the utility. This will not be an issue under today's high speed networks. The only requirement is that the game stage duration should be greater than the worst case end-to-end delay in the network. In addition, we assume that the medium is error free. Even if it is not the case, reliable transport protocols can solve the problem using re-transmissions. Again, we only have to increase the game stage duration to account for extra retransmission delays. We believe this slightly affects the overall performance of the algorithm since it takes the proposed algorithm only 6 stages to converge. Moreover, to avoid communication peaks that would happen when all players send their schedules to the utility at each stage, we can increase the game stage duration and adopt an algorithm that causes players to send their schedules at different times but still within the stage duration.

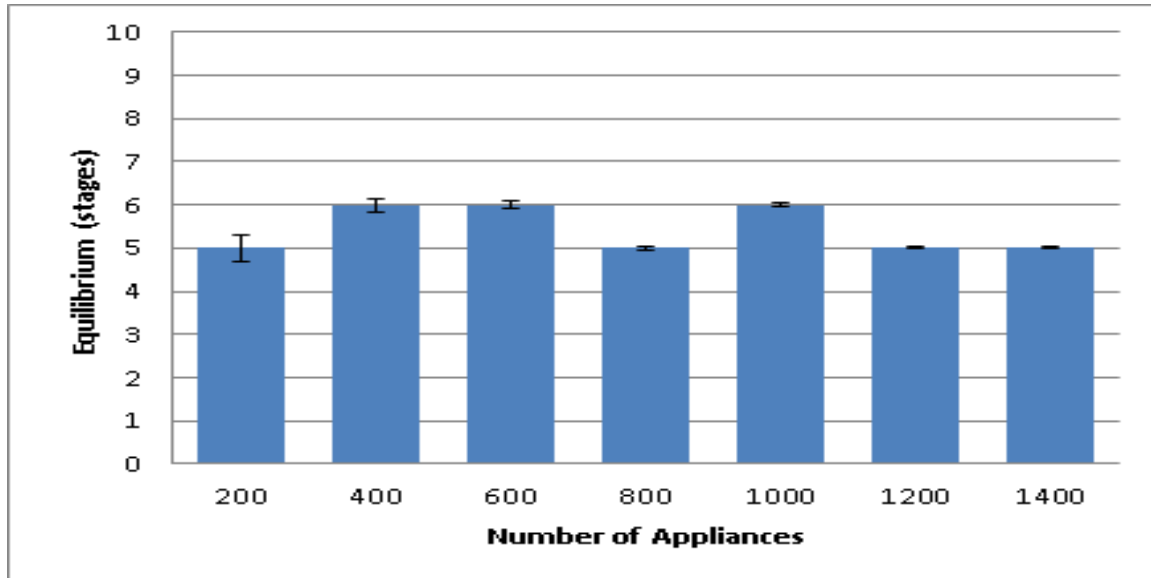


Figure 3.7: Equilibrium Time vs. Number of Appliances

3.6 Conclusion

In this chapter, we proposed a demand management algorithm based on a modified regret matching procedure in order to balance the overall residential loads while enhancing the consumers' savings and preserving their comfort. The proposed algorithm differs from other demand management mechanisms by giving the user the possibility to prioritize the comfort or the savings. It also takes into account various types of appliances (hard, soft-consecutive/non-consecutive). Based on extensive simulations, we showed that the proposed algorithm efficiently distributes the load, and achieves lower electricity bills compared to uncontrolled energy consumptions. We have also analyzed the performance of the algorithm under various scenarios where the type, the number of appliances, and the weighting factor are changed. The algorithm convergence in reasonable times and is able to reach significant savings as shown in the results. Finally, we compared the performance of the proposed algorithm to a centralized approach that calculates the optimal solution, and find out it gets up to 96% closer to the optimal solution.

In the next chapter, we plan to extend the proposed algorithm to be used in the presence of multiple energy resources. We also study the issue of fairly dividing the costs stemming

from using the shared resources.

Chapter 4

Fairness-Aware Game Theoretic Approach for Demand Response

Demand response programs are implemented by the utilities to manage the energy consumption at consumer side. Demands are managed in response to supply conditions as opposed to the traditional grid. The existing programs focus mainly on achieving system objectives such as minimizing peaks and reducing the cost of power generation. Consequently, users' electrical bills will be reduced but the question of fairness has barely been discussed in the literature.

In this chapter, the issue of fairness within demand response programs is addressed. In this context, a fair pricing model based on the contribution of each user toward attaining the aggregated system cost is proposed. In addition, the proposed system considers a more realistic scenario that consists of multiple energy sources within a microgrid as opposed to existing ones that use only one shared energy source.

We first employ the concept of Shapley value in the pricing model to evaluate the fairness of existing works. Then, we use an approximation of this value to drive our proposed demand response program. Finally, we evaluate the use of the approximate Shapley within our proposed demand response algorithm and compare it to existing works.

4.1 Introduction

Smart grid is the next generation electricity grid where new and advanced technologies are being integrated within all components of the grid. Enhancing the efficiency and reliability of the power grid, improving power quality, and saving energy are the main objectives of the smart grid. It provides two-way communication and power flow between suppliers and consumers to automate power delivery. It also employs pervasive computing capabilities to afford improved power control, monitoring, and protection of interconnected elements within the grid [142]. The smart grid introduces the use of multiple micro-generation devices such as rooftop solar panels and wind turbines across residential areas. This has great effect on environment protection, energy availability and diversity, and the economy [143]. However, renewable distributed energy resources undergo wide fluctuations depending on different factors such as weather conditions. Therefore, it is very challenging to integrate these resources into the grid as its efficiency and reliability will be affected.

To solve the coordination between these distributed resources and the grid, the idea of dividing the smart grid into various subsystems was proposed [144]. Each subsystem is called a smart microgrid and consists of a group of local generators, loads, and storage devices that are able to manage and control themselves. The microgrid can either operate by itself under island mode or can be connected to the main electric grid. The recent spike in energy consumption, due to the integration of electric vehicles for instance, can put an enormous load on the grid, leading to consumer equipment damage, power quality degradation or even blackouts. To overcome these new challenges and to increase the microgrid robustness and resilience, sophisticated mechanisms that manage and schedule residential loads are needed. In fact, demand management is a mechanism applied to match the total demands to the available supply, either by reducing consumption during peak hours or by shifting energy demands to off peak hours [145].

Besides managing the load, billing the users is a challenging concept associated with demand response. It is clear that the price should depend on the amount of energy consumed and the overall system load. However, the crucial parameter that affects the price paid by each user is its contribution to the total system cost. Users will be encouraged

to cooperate with each others and participate in demand response when the price they pay is tied to their contribution. In the presence of multiple resources with different costs, sharing the system total cost among the users becomes more challenging. For instance, a user requiring a high amount of energy might push the system to use an extra energy resource at a higher cost, causing a surge in the price. Therefore affecting all users even those who consume a very small of energy. Charging such users at the same rate as those causing the price surge is considered unfair. In fact, this problem fits very well in the cost-sharing model where users must fairly divide the total cost based on their responsibility in increasing the unit of energy cost (wholesale price).

Demand response within the smart grid has been extensively investigated since the emergence of the smart grid concept. The different proposed approaches are generally based on optimization or game theory. A comprehensive survey can be found in [93]. These approaches differ mainly in their objectives. Some aim to minimize the total energy generation cost, while others focus on minimizing the peak-to-average ratio. However, most of them do not consider fairness among customers. To the best of our knowledge, the only work that discussed fairness is [94], [95], [96], [97], [101], [102], and [103].

In [95], fairness is tackled from a social perspective. The authors propose a scheme where users pay for electricity depending on their income. In [94], the authors propose a centralized billing scheme where users are billed based on their flexibility in purchasing delay. The authors in [96] propose a fair mechanism to schedule users' loads based on a water-filling method. Fairness in this context is defined as assigning the same long-term average delay to all users. In [101] and [102], the concept of adjusting the price paid by each user before the actual scheduling of demands is proposed. This is used a way to penalize users that deviate from the calculated schedules in order to incorporate a fair billing.

In [103], the authors propose an estimation to the Shapley value using a reinforcement learning algorithm that approximates optimal stratified sampling. The authors study different techniques for sampling and approximating the Shapley value. Then, they use these techniques within a demand response program to compensate users by splitting the generated revenue in a fair manner. As opposed to our work, the authors split the revenue

generated from coordinating their energy usage in order to reduce the energy cost. The goal is to reward users that reduce their load as a result of enrolling in the demand response program.

Finally, in [97] the authors propose a billing scheme where a consumer pays a ratio of the total system bill that is equal to the ratio of its consumed energy to the system energy. However, most of these schemes assume a single shared source of energy. Those assumptions do not hold for practical microgrid systems

As the main differences between the smart grid and the microgrid is the presence of local energy resources owned by the microgrid. Only when demands within the microgrid becomes higher than the local supply, energy is used from outside the microgrid, usually at a higher price. In addition, the operation and maintenance costs associated with these energy resources vary depending on their types. For instance, the average power plant operating expenses in 2012 was 3.189 cents/kWh for Fossil Steam and 1.134 cents/kWh for Hydro-electric [146]. Therefore, the adopted pricing scheme should incorporate the effect of multiple energy sources with different costs, and most importantly how to fairly bill users in such a scenario.

In this chapter, we use the microgrid architecture in Figure 4.1 where multiple households, equipped with smart appliances, share various types of energy resources within a residential area. Each smart appliance can either communicate directly with the microgrid controller or via a smart meter installed in each household. The local controller orchestrates the load management within the microgrid. Upon receiving the demands from appliances, it calculates the total energy required and decides which resources are needed to satisfy these demands. To be environmentally friendly and reduce the system cost, the microgrid controller will always start by using cheaper renewable energy resources. It allows energy to flow from expensive external resources (e.g. main electric grid) only when the demand exceeds the supply of local energy resources. We consider the randomness in generation associated with renewable energy sources to be out of the scope of this chapter.

We focus on a microgrid environment and assume the following:

- Multiple sources of energy (such as wind turbines, solar panels, and hydro power)

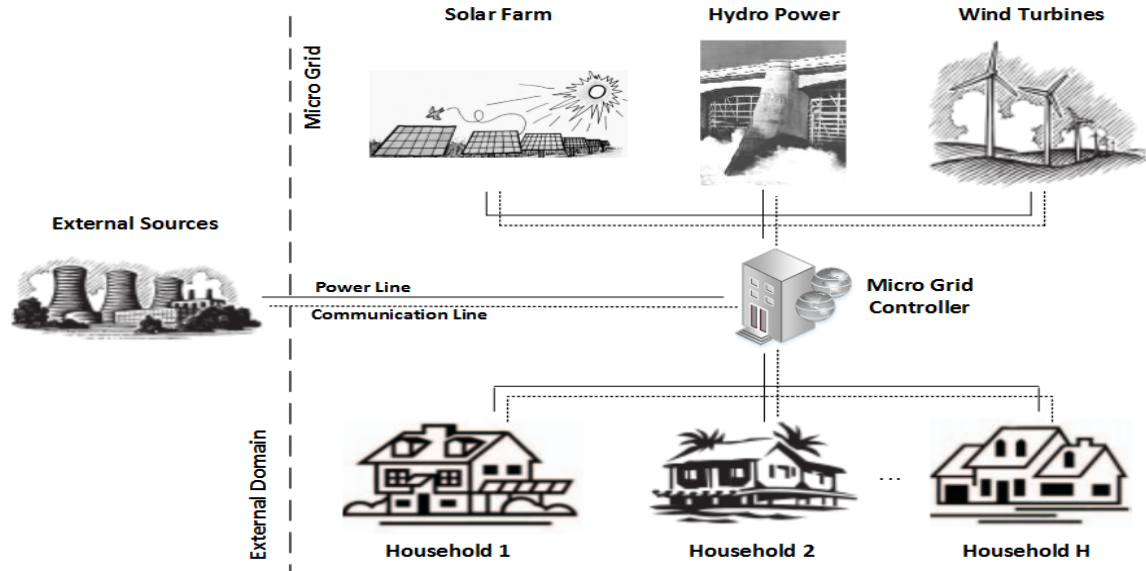


Figure 4.1: Microgrid Example Architecture

exist in the microgrid.

- There is a per kWh price associated with using each energy source including external ones, and each energy source has a maximum generation capacity.
- Users have equal access rights to energy and can use as much energy as needed.
- Communication delays and errors are negligible.

In this chapter we propose a fair billing mechanism that rewards the users based on their contribution in achieving the overall system cost. To ensure fairness among users we will employ the concept of Shapley value [147], used in game theory, to calculate the exact price paid by each user. The Shapley value was introduced by Lloyd Shapley as a way to assess the benefits a player would get from playing a game beforehand. The individual payoff is determined according to how much the player brings to the coalition by its participation. In this context, the Shapley value can be used to calculate the fair share of each user exploiting the shared micro grid resources. By binding the contribution of a player with a fair value, we encourage and incentivise him to cooperate with others. Since the Shapley value allocates shared costs fairly among users, we adopt it as a benchmark. Unfortunately, the Shapley value cannot be efficiently used in systems of more than tens of users [148].

Therefore, we propose the use of an approximation of the Shapley value proposed in [148] to overcome this limitation. This approximation is based on sampling technique, where only a sample size of the population is selected to calculate the Shapley of each user. Then, we integrate this fair billing mechanism within a demand response program, which is able to balance the load and reduce the total energy cost by preventing peaks and rebound peaks from happening. By incorporating fairness within demand response, we will not only provide a fair billing mechanism among the users but we will also incentivise them to take part of the demand response program. As simulation results show, by sending an accurate price signal to the customers, we drive their cooperation into achieving better system savings, avoiding rebound peaks, and fairly sharing the total system cost.

The rest of this chapter is organized as follows. Section 4.2 presents the system model. We then propose the fair billing mechanism in Section 4.3. Performance evaluation results are shown in Section 4.4 while Section 4.5 concludes the chapter.

4.2 System Model

4.2.1 Power System

We consider a microgrid in a residential neighborhood as shown in Figure 4.1. Each user is having a number of appliances. The set of appliances in the system is defined as $\mathcal{N} = \{1, 2, 3, \dots, n\}$, where n is the total number of appliances. We divide the time into equal timeslots H such that $H \in \mathcal{H} = \{1, 2, 3, \dots, h\}$. We set each timeslot to one hour for simplicity purposes. Each appliance $N \in \mathcal{N}$ is considered to have an energy consumption schedule as follow:

$$x^N = [x_1^N, x_2^N, \dots, x_h^N]. \quad (4.1)$$

where the x_H^N represent the amount of energy required by appliance N in timeslot H .

As opposed to our previously proposed work in Chapter 3, we will only consider flexible (soft non-consecutive) appliances since the scope of this chapter is to propose a fair billing and not to model the user's comfort. However, it is worth noting that the comfort can

Table 4.1: Table of Notations

Symbol	Description
x^N	Energy consumption schedule for appliance N
B^N	Energy bill of appliance N
\mathcal{R}	Set of local energy resources
$\mathcal{R}ext$	Set of external energy resources
R_{cap}^i	Generation capacity of R^i (kWh)
R_{cost}^i	Cost of energy generation of R^i (cent/kWh)
$C_H(L_H)$	Energy cost per time slot H
U_t^N	Payoff received by appliance N at stage t
Sh_N	Shapley value of N
\hat{Sh}	Estimated Shapley value of N
$\mathcal{C}(S)$	Cost of coalition S
m	Minimum sample size
rng	Maximum range of the marginal contribution
ϵ	Error bound of the approximation
σ	Failure probability of the bound

be incorporated into the fair billing mechanism. See Chapter 3 for more details about modeling user's comfort and preferences in demand management.

At the generation side of the microgrid in Figure 4.1, we consider that each local energy resource R^i such that $R^i \in \mathcal{R} = \{R^1, R^2, R^3, \dots, R^r\}$ is associated with generation capacity R_{cap}^i kWh and cost R_{cost}^i cent/kWh. When the demands exceed the local microgrid energy supply, the microgrid controller can allow energy to flow from external sources $\mathcal{R}ext$ such that $\mathcal{R}ext \in \mathcal{R}ext = \{\mathcal{R}ext^1, \mathcal{R}ext^2, \mathcal{R}ext^3, \dots, \mathcal{R}ext^r\}$ such as the main electric grid or neighboring microgrids. Obviously, the cost associated with such external sources is more expensive than local ones. We denote $\mathcal{R}ext_{cap}^i$ in kWh and cost $\mathcal{R}ext_{cost}^i$ in cent/kWh as the generation capacity and the cost associated with external source $\mathcal{R}ext^i$, respectively.

Algorithm 2 Demand Response Algorithm for Player $N \in \mathcal{N}$

Input: Set of s energy consumption schedules \mathcal{S}^N .

Output: The sub-optimal schedule s^N for player N .

- 1: randomly select an initial energy consumption schedule s_1^N , set $t = 1$;
 - 2: **repeat**
 - 3: send schedule s_t^N to the controller
 - 4: receive B^N and $\sum_{H=1}^h C_H(L_H)$ from the controller
 - 5: compute the payoff based on equation (4.2)
 - 6: compute the regret based on equation (4.3)
 - 7: select the next action/schedule based on equations (4.5) and (4.6)
 - 8: **if** same action/schedule chosen in the past 10 rounds **then**
 - 9: exit loop
 - 10: **else**
 - 11: $t = t + 1$
 - 12: **end if**
 - 13: **until** no player changes his energy consumption schedule
-

The microgrid controller is responsible for calculating the cost of the energy needed to satisfy the demands. In order to ensure a lower system cost, the controller will check the availability of cheaper resources in \mathcal{R} first, then move to more expensive external resources in \mathcal{R}_{ext} only when needed. This means that the pricing/billing scheme will not be uniform as the energy unit price depends on the total system load, which determines the energy resources to be used. As long as demand response programs are able to reduce the energy bill of the users and provide a fair billing mechanism, we believe that users will have more incentives to collaborate and take part of the demand response program.

4.2.2 Energy Consumption

The adopted demand response mechanism is based on game theory where players (appliances) execute a modified regret matching reinforcement procedure [137]. The game is repeatedly played over a number of fixed periods called stages as illustrated in Algorithm

2. Each player chooses between a number of different energy consumption schedules. More precisely, during each stage t , player N makes a move by choosing a specific consumption schedule $s_t^N \in \mathcal{S}^N$ such that $\mathcal{S}^N = \{1, 2, 3, \dots, S\}$. This set consists of the different possibilities of shifting the player's energy consumption to different timeslots denoted as the set of available actions for player N where S is the total number of actions/schedules. Each action a player chooses is associated with a specific payoff U_t^N according to (4.2). The objective of each player is to maximize its own payoff. Then, each player calculates an average regret $Q_t^N(j, k)$ of choosing a given action j instead of k according to (4.3), and uses this regret to choose the next stage's action according to probabilities (4.5) and (4.6).

The payoff for player N at stage t (U_t^N) is defined as follows:

$$U_t^N(s_t^N, s_t^{-N}) = -\frac{B^N}{\sum_{H=1}^h C_H(L_H)} \quad (4.2)$$

where s_t^N represents the actions selected by player N at stage t and s_t^{-N} the actions selected by all other players except N .

$$Q_t^N(j, k) = \max\{C_t^N(j, k), 0\} \quad (4.3)$$

where

$$C_t^N(j, k) = \frac{1}{t} \left[\sum_{\tau \leq t: s_\tau^N = k} \frac{p_\tau^N(j)}{p_\tau^N(k)} U_\tau^N - \sum_{\tau \leq t: s_\tau^N = j} U_\tau^N \right] \quad (4.4)$$

Equation (4.3) is an estimation of how much player N regrets at stage t for not selecting energy consumption schedule k instead of j in the past. It basically measures the difference (strictly speaking, its positive part) of the average payoff over the stages when consumption schedule k was selected and the stages when consumption schedule j was selected. If at stage t , player N selects an action j , the probability of choosing action $k \neq j$ in the next stage is approximately proportional to the calculated average regret from j to k and is depicted in (4.5). Action j is chosen again in the next stage with the remaining probability as in (4.6). More information about the demand response Algorithm 2 can be found in section 3.4.2. The following variables are chosen as follows: $0 < \delta < 1, 0 < \gamma < 0.25, \mu >$

$2M^N(S-1)$ for all N , where M^N is an upper bound on $|U^N(s)|$ for all $s \in \mathcal{S}^N$. Proofs and explanation for this choice can be found in [137] and are out of the scope of this chapter.

$$p_{(t+1)}^N(k) = \left(1 - \frac{\delta}{t^\gamma}\right) \min \left\{ \frac{1}{\mu} Q_t^N(j, k), \frac{1}{S-1} \right\} + \frac{\delta}{t^\gamma S} \quad (4.5)$$

$$p_{(t+1)}^N(j) = 1 - \sum_{k \in \mathcal{S}^N: k \neq j} p_{(t+1)}^N(k) \quad (4.6)$$

To calculate the payoff (4.2), each player needs only to know its own share of the bill B^N and the total system cost $\sum_{H=1}^h C_H(L_H)$, where L_H is the total system load per timeslot H . The microgrid controller, after it receives all the players' consumption schedules, calculates the cost $C_H(L_H)$ per timeslot H , then aggregates it over all the hours $H \in \mathcal{H}$ in order to figure out the $\sum_{H=1}^h C_H(L_H)$. However, calculating B^N in a fair manner is challenging. Basically, the players share the total system cost and each one of them must pay a part of it based on his contribution. For illustration purposes, let's assume we have two energy resources, such that $\mathcal{R} = \{R^1, R^2\}$, each associated with a different cost, and only two users in the system that use only two appliances such that $\mathcal{N} = \{1, 2\}$. We set x_H^1, x_H^2 as the amount of energy consumed by appliances 1 and 2 respectively. If $x_H^1 + x_H^2 \leq R_{cap}^1$, the total cost of the system can be divided proportionally between both users since they both use the same R_{cost}^1 using (4.7).

$$B_{propo}^N = \sum_{H=1}^h C_H(L_H) \times \frac{x_H^N}{\sum_{M=1}^N x_H^M} \quad (4.7)$$

More importantly, in the case where $x_H^1 + x_H^2 > R_{cap}^1$, the controller must use an additional resource R^2 which has an associated cost R_{cost}^2 . The question then becomes: how do we fairly share the total cost between both users in this case. The price hike in this case is due to the introduction of R^2 , but what is the contribution of each user in that hike. Contribution here signifies which user has more effect on the achieved total cost; that particular user must pay more. Unfortunately, the simple proportional approach in (4.7) does not consider this effect. Therefore, it cannot guarantee fairness under these

circumstances. A more sophisticated approach that takes into account the contribution each user brings into increasing the cost of energy is needed.

In the next Section, we define the fairness concept and Shapley value, and then show how they can be used to provide a fair billing mechanism within our demand response program.

4.3 Fair Billing Mechanism

4.3.1 Introduction to Fairness

In an effort to define fairness, Moulin writes “Justice is blind, and fairness requires anonymous rules of arbitration. Equals should be treated equally, and unequals unequally, in proportion to relevant similarities and differences” [147]. The interesting point here is to draw our attention to the “relevant” similarities and differences. *Equal treatment of equals* is a crystal clear statement. If two persons have characteristics that are identical in all relevant dimensions, they should be treated in the exact same manner. This means that they should receive exactly the same share of goods, of power, or of whatever they are distributing amongst each other. *Unequal treatment of unequals*, however, is pretty vague and can be subject to different interpretations. The definition of “relevance” is guided by four principles: exogenous rights, compensation, reward, and fitness.

To better understand these, consider the problem where a flute must be given to one of four children. The first does not have as many toys as the other three, and so he should get the flute by the principle of compensation. The second worked hard at cleaning and maintaining it, and so he should get it by the principle of reward. The third is the flute’s owner child, and so has the right to claim it. The fourth child is a flutist, and so he should get the flute because everyone enjoys the music (fitness principle) [147].

Moulin [147] defines these principles as follows:

- Exogenous rights: Equal exogenous rights correspond to equality ex ante, in the sense that we have an equal claim to the resources regardless of the way they affect our

welfare and that of others. To relate to the flute story, ownership is independent from the consumption of the flute as well as the related questions of who needs it, who deserves it, and who makes the best use of it.

- Compensation: Certain differences in individual characteristics are involuntary and affect the distribution of a higher-order characteristic that we consider to equalize. This justifies unequal shares of resources in order to compensate for the involuntary difference in the primary characteristic. For example, nutritional needs are different for infants, pregnant women, and adult males. This justifies that they would receive different shares of food.
- Reward: Prizes are given to outstanding individuals based on their contributions or sacrifices. Differences in individual characteristics are morally relevant when they are viewed as voluntary actions. They justify unequal treatment. For instance, past sacrifices justify large share of resources in the present (veterans). Reckless drivers pay more for insurance. Merit for exceptional achievement also justify rewards: prizes are given to inventors, athletes, peacemakers . . .
- Fitness: Resources must go to whomever makes the best use of them. In this case, the flute must be given to the flutist, a book in French to whomever can read French, and so on. Fitness justifies unequal treatment independently of needs, merits or rights. It can be expressed in two conceptually different ways, sum-fitness and efficiency fitness. Sum-fitness allocates resources in a way that the total utility of all concerned agents is maximized. Efficiency-fitness (also called efficiency, or Pareto optimality) is a more general concept that typically imposes much looser constraints on resources allocation. Simply put, it means that resources are divided in a way that it is impossible to make any one individual better off without making at least one individual worse off.

Consider a simple model for fair distribution. There exists a certain amount t of a commodity that needs to be divided among a number of agents, where each of these agents a is endowed with a claim c_a . If the commodity is “good”, meaning is a valuable resource,

c_a is called the demand of agent a . If it is “bad”, such as a cost to be shared as is the case of a tax, we call c_a a liability. The resource to be shared t may differ from the total sum of claims c , in which case each agent’s demand is either met or a liability is assigned to each agent. When t is smaller than c , we refer to a deficit. When it is larger, we refer to an excess situation [147]. In our case, the common use and sharing of resources entails an increase in energy prices for different agents in the system. The overall energy bill resulting from jointly using and sharing the multiple resources in the system needs to be ‘fairly’ divided amongst the agents. This problem is referred to as the problem of the commons.

A commons is a technology that is used jointly by a particular set of agents. The problem of the commons states the need to organize fairly and efficiently the exploitation of the commons. The sharing of joint costs falls squarely within the scope of the commons problem. In a cost-sharing model the agents demand certain services that are jointly produced by the commons, and they must fairly share the total cost of meeting these demands [147]. Sharing the total system cost in section 4.2.2 is a perfect example of the cost-sharing model. In this sense, the focus shifts almost exclusively on the interpretation of reward: How can individual responsibilities in the formation of the total cost be fairly assessed? Equal exogenous rights are always assumed, Compensation is absent from the discussion and Fitness is not an issue assuming inelastic demand of output or supply of input.

The basic model of the commons was introduced many years ago by von Neumann and Morgenstern’s Theory of Games [149]. In the jargon of game theory, it is also known as the model of cooperative games with transferable utility. The Shapley value represents an axiomatic solution to the cost-sharing model of the commons.

4.3.2 The Shapley Value

Within the context of the Shapley value and the problem of the commons, the focus becomes almost exclusively on the interpretation of reward. The question that needs to be answered is: what is a fair assessment of individual responsibilities in the formation of

the total cost or surplus? In this model, equal exogenous rights are always assumed and so compensation is completely absent from the discussion. Moreover, fitness is not an issue assuming inelastic demand of output or supply of input.

The Shapley value has been axiomatically characterized in different ways, four of which are presented here. Originally, there were three axioms: equal treatment of equals, dummy and additivity.

- Equal treatment is simply the translation of equal exogenous rights in the cost sharing problem as previously discussed. This means that equal agents incur the same cost when being part of a coalition that does not contain both of them.
- The dummy axiom, however, requires that a dummy agent that does not change the cost of a coalition when taking part of it, does not pay anything.
- The third axiom, additivity, is motivated as a decentralized property and also the most mathematically extensive. The additivity axiom requires that cost shares depend additively on the cost function. As an example, the cost function may be made up of two costs: a one-time installation fee and a variable maintenance cost. Note that these costs do not have to be the same and may differ from one agent to the other in the coalition.

Another characterization of the Shapley value that replaces both the dummy and additivity axioms by a single property is called Marginalism. It states that an agent's cost share depends only on the list of his marginal contributions to all coalitions. And so the Shapley value can be defined as a function of an agent's marginal contributions only. The Shapley value is the only solution for cooperative games that satisfies the dummy, additive, and equal treatments axioms, which involve a fixed size population. In contrast, two other axioms exist which rely on a variable size population.

- The first is termed Equal Impact. The impact of removing agent a on agent b 's share is the same as the impact of removing agent b in agent a 's share.

- Potential, is the other axiom and, is related to equal impact. Simply put, the potential function makes it possible to implement the marginal contribution idea. It eliminates the possibility that the solution (allocations) might not be feasible, or if feasible, might not be efficient.

The Shapley value is the only solution that satisfies potential and equal impact, and this explains why it has been widely used to solve different fairness problems. More details about the characteristics and properties of the Shapley value, as well as proofs, can be found in [147].

Under the cost-sharing context, the model specifies the set of agents $\mathcal{N} = \{1, 2, \dots, n\}$, and for each non-empty set (coalition) S of \mathcal{N} , there is a stand-alone cost $\mathcal{C}(S)$ of serving the coalition S . Let \mathcal{A}_N be the set of coalitions not containing agent N , and $\mathcal{A}_N(s)$ the subset of \mathcal{A}_N containing the coalitions of size s ($0 < s < n$).

The Shapley value assigns the following cost to agent N :

$$Sh_N = \sum_{s=0}^{n-1} \sum_{S \in \mathcal{A}_N(s)} \frac{s!(n-s-1)!}{n!} \{\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)\} \quad (4.8)$$

The last part of equation (4.8) $[\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)]$ is the difference that an agent N makes to the value of a given coalition S , known as its marginal contribution. Hence, the Shapley value provides a fair cost share of each agent in the coalition of agents sharing the total system cost. More precisely, Sh_N represents the bill paid by each appliance N or B^N in (4.2).

We have opted for the use of the Shapley value because it is the only solution known to satisfy the previously discussed axioms: *equal treatment of equals*, *dummy*, and *additivity*, as well *potential* and *equal impact*. Within the context of demand response and the sharing of microgrid resources, equal treatment of equals is the translation of equal exogenous rights in the cost-sharing problem, meaning any two users consuming the same amount of energy must pay the same bill. The dummy axiom requires that a dummy user pays nothing, and this is true for users who do not use the shared resources. Additivity requires that individual costs depend additively on the cost function, which in our case is made of up of different costs stemming from the different resources used within the microgrid.

4.3.3 Approximating the Shapley Value

Unfortunately, the Shapley value is known to be computationally complex ($\mathcal{O}(2^n)$ for one agent since the number of subsets of the set $N = \{1, 2, 3, \dots, n\}$ of agents is 2^n). Hence, computing it for one agent is very challenging since we need to compute its marginal contribution to all subsets of a given coalition. As the number of agents increases, the number of combinations grows exponentially limiting the application of the Shapley value to games with a small number of players. There have been many proposals in the literature to calculate the exact Shapley value using as few resources as possible including memory and processing power. However, they all failed to provide a calculation method that runs in polynomial time and does not need a substantial amount of memory as the set of players grows larger.

In order to overcome these problems, researchers shifted their focus into providing an approximation or estimation of the Shapley value that runs in polynomial time and does not use a substantial amount of memory, still providing a close approximation to the real Shapley value. One of these methods suggest the use of sampling techniques to approximate the Shapley value.

In particular, [148] proposes a sampling-based approach named ApproShapley that provides a polynomial-time calculation of the Shapley value. We choose their sampling method for two reasons:

- First, the complexity of the ApproShapley algorithm is polynomial (not considering the complexity of the characteristic function, which in our case is also polynomial)
- Second, they provide a bound on the approximation of the Shapley value.

In addition, they have shown that their proposed algorithm is compatible with different coalitional problems that are similar to our problem.

Sampling-based methods approximate the Shapley value in polynomial time by randomly drawing samples from the population. According to [148], the number of samples needed to approximate the Shapley value depends on three factors:

- (i) the maximum range rng of the marginal contribution among all players
- (ii) the error (bound) ϵ of the approximation, and
- (iii) the failure probability σ of this bound.

The minimum required sample size m to estimate the Shapley value with probability at least $(1 - \sigma)$ and an estimation error $\epsilon > 0$ is:

$$m \geq \left\lceil \frac{\ln(\frac{2}{\sigma})rng^2}{2\epsilon^2} \right\rceil \quad (4.9)$$

Note that m is the largest sample size among all players and needs only to be calculated once using rng . The estimation can be interpreted as follows: We need at least m samples for the estimated Shapley value \hat{Sh} to be correct within $\pm\epsilon$, $x\%$ of the time where $x = 100 \times (1 - \sigma)$, i.e. $Pr(|\hat{Sh} - Sh| \geq \epsilon) \leq \sigma$.

In order to calculate the sample size m , we need to calculate the maximum range rng of the marginal contributions among all players:

$$rng = \max_{N=1}^n \left[\max_{S \subset \mathcal{A}_N \setminus \{N\}} \{\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)\} - \min_{S \subset \mathcal{A}_N \setminus \{N\}} \{\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)\} \right] \quad (4.10)$$

Obviously, the range of an agent N is the difference in the maximum and minimum marginal contributions N pays as being part of a coalition. The maximum marginal contribution of an agent occurs when he pays a maximum price, i.e. uses energy from the most expensive resource. Similarly, the minimum contribution occurs when he pays a minimum price. Hence:

$$\max_{S \subset \mathcal{A}_N \setminus \{N\}} \{\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)\} = \max_{j=1}^{r_{ext}} R_{cost}^j \times \sum_{H=1}^H x_H^N \quad (4.11)$$

and:

$$\min_{S \subset \mathcal{A}_N \setminus \{N\}} \{\mathcal{C}(S \cup \{N\}) - \mathcal{C}(S)\} = \min_{j=1}^r R_{cost}^j \times \sum_{H=1}^H x_H^N \quad (4.12)$$

therefore:

$$rng = \max_{N=1}^n \left[\left(\max_{j=1}^r R_{cost}^j - \min_{j=1}^{r_{ext}} R_{cost}^j \right) \times \sum_{H=1}^H x_H^N \right] \quad (4.13)$$

Once the sample size has been determined, the estimated Shapley value can be calculated according to Algorithm 3 in polynomial time. In order to get a better estimate, we

Algorithm 3 Calculation of $\hat{S}h_N$

```
1: Calculate  $m$ .
2:  $count = 1; \hat{S}h_N = 0; \forall N \in \mathcal{N}$ 
3: for  $count = 1$  to  $m$  do
4:   Take a random  $\pi$  permutation in  $\Omega$ 
5:   for  $N = 1$  to  $n$  do
6:      $\mathcal{C}_N = \mathcal{C}(Pre_N(\pi) \cup \{N\}) - \mathcal{C}(Pre_N(\pi))$ 
7:      $\hat{S}h_N = \hat{S}h_N + \mathcal{C}_N$ 
8:   end for
9:    $count = count + 1$ 
10: end for
11:  $\hat{S}h_N = \frac{\hat{S}h_N}{m} \forall N \in \mathcal{N}$ .
```

have slightly modified the way samples are drawn. We make sure that the random samples are drawn from the different coalition sizes to ensure that the approximate Shapley value is calculated from all different sizes of coalitions. This is done by randomly choosing m samples from permutations set Ω (where the cardinality of Ω is a polynomial in n). The $Pre_N(\pi)$ represents the set of nodes that occur before the node N in a permutation π . Computational time can be saved by storing each evaluation of the cost function so that each unique coalition that corresponds to any permutation is not evaluated more than once.

4.4 Performance Evaluation

4.4.1 Simulation Settings

In order to assess the effect of using ApproShapley within the proposed demand response program, we simulate a microgrid with a different number of users and appliances using OMNET++ [141]. We randomly choose a number of appliances per user between 1 and 10 based on uniform random distribution. We also randomly choose the energy usage for

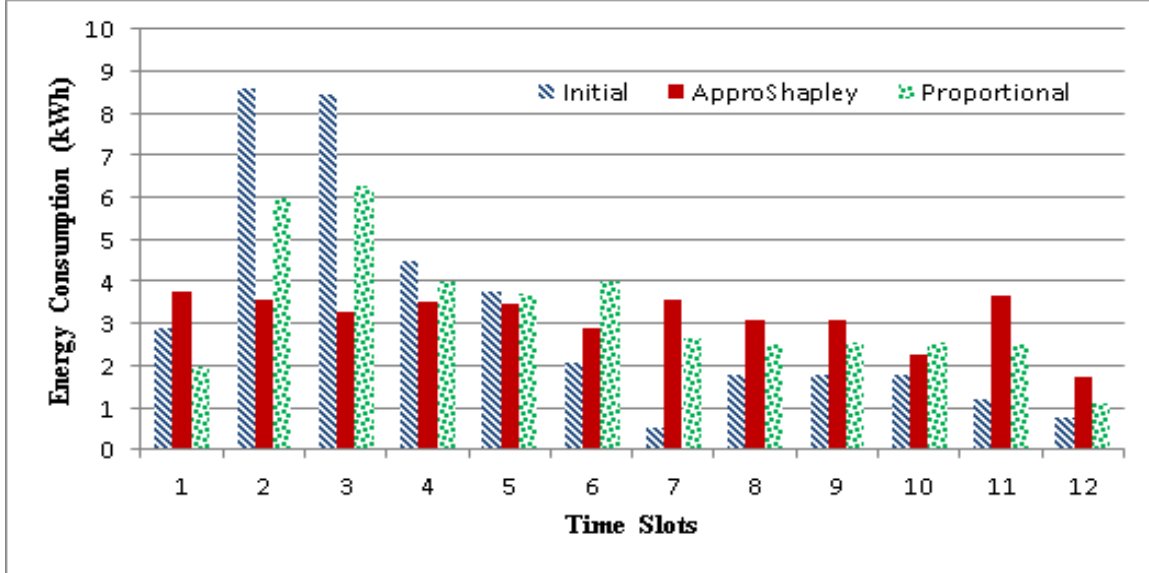


Figure 4.2: Total Hourly Energy Consumption

each appliance according to [150]. Electricity prices for different energy sources (both local and external) were set according to [146].

In all simulations, local energy sources cover 70% of the total microgrid demand, and are divided into renewable and hydro-electric. The remaining 30% is covered by an external nuclear generator at a higher cost. We choose the following for sample size calculation: $\epsilon = 0.01$ and $\sigma = 0.05$, which means that the estimation will be off by 0.01 95% of the time.

4.4.2 Simulation Results

First, we evaluate the proportional billing mechanism by comparing it with the Shapley value calculation. In this first scenario, the total number of users is 10 and each user has only one appliance. Table 4.2 clearly shows that the proportional mechanism favors some users over others. For instance users 1, 2, 5 and 10 pay more using proportional billing whereas the other users pay less. Note that in the case of 10 users, ApproShapley turns out to be the same as Shapley since the number of samples is greater than the population size.

Table 4.2: Fair Billing: Shapley vs. Proportional

User	Proportional (¢)	Shapley (¢)	Offset (¢)
1	110.51	98.92	11.59
2	125.67	115.34	10.33
3	83.48	88.16	-4.68
4	85.63	91.12	-5.50
5	80.02	79.91	0.12
6	73.00	75.93	-2.93
7	88.24	91.97	-3.73
8	195.45	201.73	-6.29
9	147.80	153.07	-5.28
10	31.74	25.38	6.36

Figure 4.2 illustrates the changes in the total hourly energy usage of a microgrid of 20 users running the demand response algorithm 2 using the estimated Shapley to calculate the payoff compared to using the proportional scheme. We notice that using the estimated Shapley as a billing mechanism, to send back the price signal to the players, flattens the load better across all timeslots. Hence it is a good candidate for use in the demand response program. Notice that Figure 4.2 shows the total hourly usage across the timeslots. It is important to note that the proposed demand response program does not reduce power consumption, but rather helps in avoiding peaks and rebound peaks and flattens the load across the hours of the day, leading to savings in the system cost and users' electricity bills.

Figure 4.3 illustrates the savings achieved by the demand response algorithm using both ApproShapley and the proportional scheme. It shows that using ApproShapley better assists users in making better decisions in terms of coordinating the shifting of their schedules, hence achieving better savings and avoiding re-bound peaks. We see that the savings are as little as 21% and go up to 30% for the case of 60 users.

Figure 4.4 shows the equilibrium time which is the number of rounds it takes the

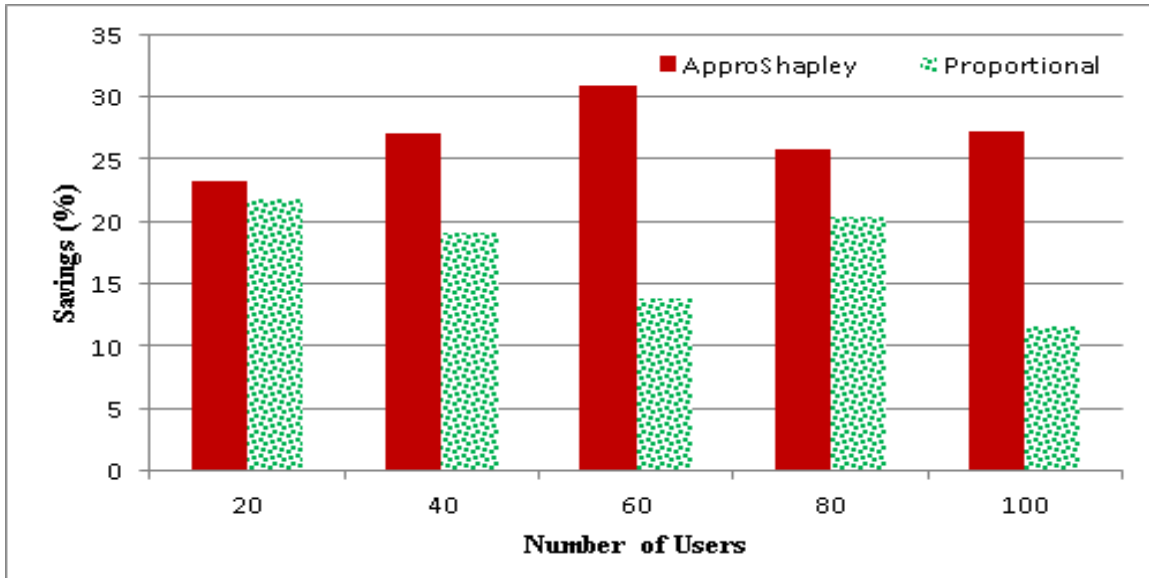


Figure 4.3: Savings vs. Number of Users

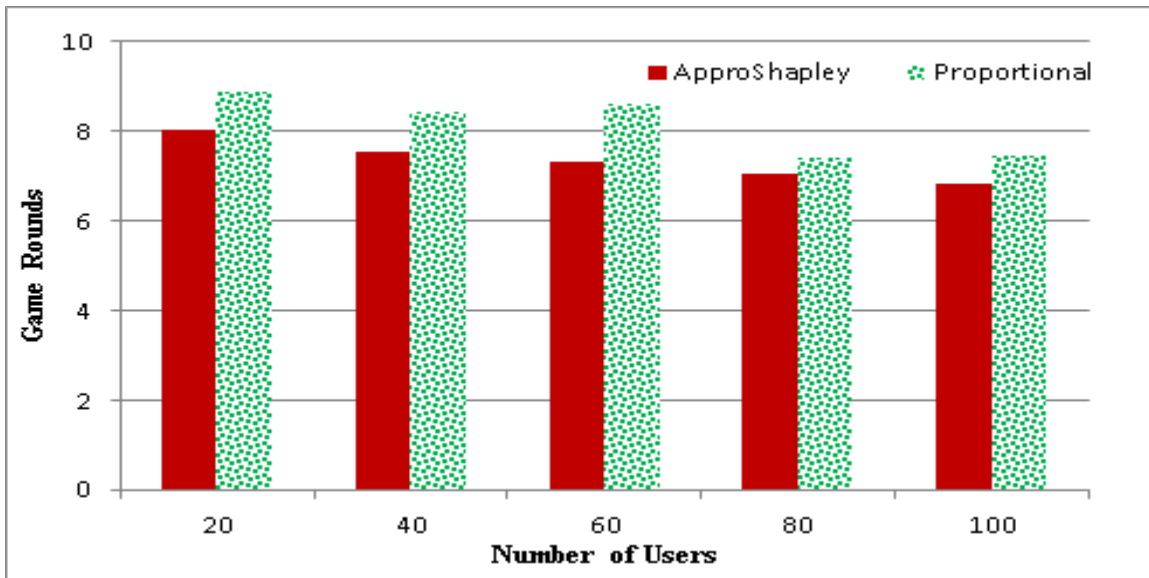


Figure 4.4: Equilibrium Time vs. Number of Users

demand response algorithm 2 to converge. Convergence happens when all players stick to their chosen action, i.e. consumption schedule, at which point the game can be stopped and a solution has been found. We notice that the equilibrium time is slightly better when using ApproShapley than when using the proportional scheme. More importantly, the proposed demand response program enables players to find a solution in about 8 games

rounds.

Estimating the Shapley value of one appliance uses the sample size m which, as shown in equation (4.9), does not depend on the population size n . Therefore, the complexity of estimating the Shapley value for all the appliances is $\mathcal{O}(mn)$.

4.5 Conclusion

In this chapter, we consider a microgrid with local (renewable or non-renewable) resources that are shared between users. The microgrid is also connected to external, more expensive resources, that are only used when needed. We introduce the problem of sharing common resources within the microgrid in a fair manner. We first introduce the concept of fairness and scope it within the problem of demand response in the microgrid.

We then propose the use of Shapley value to fairly divide the microgrid system cost between users participating in the demand response program. Then, we use a sampling based approach that approximates the Shapley value and that runs in polynomial time. The use of this ApproShapley within our proposed demand response algorithm, to send price signals to users participating in the program, helps these users in making better decisions concerning shifting their energy consumption schedules.

Using simulations, we show that using the estimated Shapley achieves better savings, helps flattening the load, and avoids peaks and rebound peaks from happening in the system. This yields to reducing the total system cost as well as individual users' electricity bills. We compare the use of the estimated Shapley within our proposed algorithm to the use of the proportional billing mechanism. Results show that the estimated Shapley provides better incentives to users participating in the demand response program.

In the next chapter, we consider a system where users are equipped with multiple local energy resources and storage capabilities, and have the ability to store the excess energy and sell it on the market. To meet their local demand, a number of geographically distributed consumers need to buy energy from their neighbors with the excess of energy stored. The extra energy could have been acquired from renewable resources at a cheaper

prices, and is then sold at higher prices to generate profit. Trading energy in the smart grid is achieved thanks to the introduction of two-way energy flow. There are many advantages to energy trading in the smart grid, including protecting the environment and decreasing the load on the main grid.

Chapter 5

Energy Trading: A Distributed Game Theoretic Approach

In this chapter, we propose both a centralized solution and a distributed game theoretic approach to solve the problem of energy trading in the smart grid. In particular, we consider a number of geographically distributed consumers that need to buy energy from neighboring users who have a surplus of stored energy, to meet their local demands. While buyers minimize their energy bill by buying energy at prices lower than that of the grid, sellers can make profit by selling the extra stored energy, which could have been acquired from affordable renewable resources. Buying energy from neighboring users also helps in reducing the stress on the main grid, which decreases electricity prices and protects the environment. We first formulate the energy trading problem as a centralized optimization problem. Then, we propose a distributed solution based on game theory that requires each user to merely apply its best response strategy to the current state of the system. Buyers play the game by deciding how much energy to buy from each seller in order to minimize their energy bill taking into account different constraints tied to the grid infrastructure. Extensive simulations confirm the effectiveness of the proposed approach in terms of energy bill savings, convergence in acceptable times, and fairness to its users.

5.1 Introduction

In this chapter, we assume that the two-way communication link between the users is reliable, with negligible delay, low error rate, and high bandwidth. We also consider that all the buyers in the system are able to locate all the available energy resources or list of sellers.

The electricity industry worldwide is trying to address different challenges of the traditional electric grid, namely demand response, reduction of greenhouse effect, energy conservation and diversification, among others. The unidirectional nature of the traditional electric grid adopts a centralized model of producing and transmitting energy, which wastes an enormous amounts of energy. The next-generation improved electricity grid, also known as the smart grid, introduces a new concept for generating electric power, known as distributed generation. It basically combines different sources of energy such as photovoltaic panels, fuel cell, and wind turbines to generate on-site reliable electric power. In addition to providing environmental benefits, distributed generation can also help in reducing the transmission and distribution loss, and relieving congestion [151]. Various challenges are facing the deployment of these renewable energy resources and energy storage units. The intermittent nature and highly variable supply makes distributed generation hard to manage. In fact, with the widespread deployment of these resources, it is difficult to effectively use their entire capacity to meet fluctuating local energy demand. Thus, new mechanisms that accommodate this intermittent behavior need to be developed. The majority of customers within the smart grid are also equipped with EVs and other storage units [152]. These new components as well as the two-way flow of communication and energy, introduced by the smart grid, open the door for developing advanced energy trading mechanisms. Consumers are becoming more environmentally aware and highly informed as opposed to passive ratepayers, which pushes them to participate in the new trend of power generation. In particular, customers can participate in decentralized energy trading by selling their surplus of energy either to the electric grid or to other consumers. They are motivated to participate in the energy trading process since they will increase their energy costs savings as well as their profits stemming from selling the surplus of energy. From the

electric grid side, energy trading will result in reducing the peak demands, which reduces the system operation cost. It will also improve the grid efficiency and reduce green house gas emissions.

In general, previous works on energy trading can be classified into several categories depending on the solution used, the involved parties, and the different objectives and constraints considered in the trading process.

Some works have addressed trading energy with a central unit such as the main grid. In [104], the authors study the feasibility of applying differential pricing scheme to offset the inconvenience experienced by an energy user during the trading process with an energy controller in smart grid. In [105], consumers are incentivized to sell their surplus of energy to the main grid during energy deficiency and peak hours. A multiagent system is proposed in [107] where each autonomous agent in a given house decides whether to buy, sell, or store energy by taking into consideration their current and expected load and generation. A negotiation model based on adaptive attitude bidding strategy for energy trading between smart buildings and the utility grid is proposed in [108]. This negotiation agent adaptively adjust the trader's decisions according to the opponent's behaviors using on particle swarm optimization. The authors in [109] propose a different approach where energy is traded between residential users, equipped with distributed energy resources and no storage devices, and an energy controller instead of the main grid. This approach is based on Stackelberg game where the energy controller minimizes its cost of purchasing energy and residential users maximize their profits by selling energy to the controller at a lower price instead of the grid. Other approaches include [106] and [111].

In the same context of trading energy with the main grid, other approaches have focused on V2G technology. For example, a V2G algorithm using dynamic programming is proposed in [153] to produce profits to vehicle owners by taking part in ancillary service markets. Another approach is proposed in [113] where the coordination of unidirectional V2G services with energy trading is used to maximize the V2G aggregator profit while maintaining the risks associated with energy trading at acceptable levels. The authors in [114] propose an energy scheduling problem in a power system where energy trading is

permitted between an aggregator and customers equipped with electrical vehicles. Both a collaborative and a non-collaborative approach are proposed. In [115], the authors propose the use of a mixed integer linear programming framework to model a HEM structure, where a distributed renewable energy generation system, V2H and V2G capabilities in conjunction with two way energy trading of energy storage systems are combined together.

Other approaches have studied trading energy between multiple microgrids operating in island mode in order to satisfy their local demands and to manage the non-dispatchable distributed energy resources within the microgrids. For instance, in [116] the energy trading problem between microgrids is explored where the surplus generated by renewable energy sources can be traded with other microgrids to reduce the reliability on the grid and the peak demands. In [117], the authors proposed a model to optimize the operation of connected microgrids where energy is exchanged between them in order to utilize the fluctuations of stochastic energy sources and demands. A similar approach is proposed in [118] where a microgrid aggregator is used to fully control the local distributed energy resources as well as the load to optimize the production of these resources and the energy exchange with the main grid. In [119], multiagent systems are used to simulate multiple microgrid market scenarios, where energy buyers and sellers are modeled as load or generation agents with and without storage systems depending on their local demands and supply. The authors in [120] used a bi-level programming to study the effect of both the price levels and demand fluctuations on the production and load curtailment. A convex optimization framework is proposed in [121] for energy trading between islanded microgrids in order to minimize the global system cost. Other approaches that use game theory include [122], [124] and [123].

Other works focus on directly trading energy among users of the smart grid without the involvement of a third-party such as the grid or an aggregator. In [125], the authors simply study the effect of the introduction of energy trading between neighbors on electricity pricing and demand response programs. Within demand response context, a centralized energy management algorithm based on linear programming is proposed in [127]. It is executed by a local energy management system to control the actions taken by a cluster of

demands such as buying, selling, and storing energy. The authors show that there exists a mechanism for profit-sharing, which stabilizes the game. In [129], the authors analyze the cooperation between small scale energy suppliers and end users in direct energy trading using coalitional game theory. Specifically, the authors analytically derive an electricity pricing scheme that achieves a fair division of revenue between energy suppliers and end users using the asymptotic Shapley value. In [128], the authors present the design and implementation of an energy market place where consumers are encouraged to form groups of sellers and buyers to sell/buy energy. A non-cooperative game is proposed in [130] where energy is traded between a set of energy storage units in order to maximize their profit by taking into consideration the accompanying cost of trading. A double auction mechanism is used to determine the trading prices in this energy market. In [131], a risk based auction with an adaptive bidding energy trading strategy is proposed, where an auctioneer manages the available distributed resources and receives bids from buyers and asks from sellers. Other auction based energy trading algorithms are proposed in [133] and [132].

In this chapter, we consider a realistic scenario where a number of users equipped with distributed generation capabilities trade energy with one another. Particularly, the extra stored energy can be used to fulfill other users' demands. Energy trading can only be achieved with the active participation of customers by incentivizing them. Therefore, as opposed to existing works that focus on determining the amount of energy to be traded and the trading price, we choose to allow the seller to have full control over these parameters. This way individual sellers' preferences are preserved. Sellers make profit by selling their extra stored energy. Buyers share the resources of the system equally which preserves fairness among them. We propose a fully distributed game theoretic approach whereby buyers choose the best sellers to buy energy from in order to minimize their energy bill. More importantly, we follow a different route and take into account the nature of the smart grid infrastructure and consider the geographical distribution of sellers and buyers. We incorporate energy transmission costs into our proposed trading mechanism. In addition, we include the physical smart grid infrastructure constraints, namely the capacity of transmission links connecting the different sellers and buyers. The performance of the proposed mechanism is evaluated using simulations, and the results are compared to a centralized

optimization model.

The contributions of this chapter are as follows:

- First, we propose a model for energy trading within the smart grid.
- Second, we propose a centralized optimization model that takes into account the physical smart grid infrastructure constraints.
- Third, we propose a fully distributed game theoretic approach to trade energy among smart grid users.
- Fourth, we perform extensive simulations to evaluate the performance of the proposed algorithm. We compare its performance against the centralized model.

The rest of the chapter is organized as follows. We present the system model in Section 5.2 and formulate the optimization problem in Section 5.3. Section 5.4 discusses the proposed distributed energy trading algorithm. Performance evaluation results are shown in Section 5.5 while Section 5.6 concludes the chapter.

5.2 System Model

We consider a residential neighborhood with multiple users equipped with distributed energy generation and storage units as shown in Figure 5.1. Users are divided into sellers and buyers. Sellers advertise their excess of energy within their storage units to the buyers that need the extra energy to meet their local demands. Let $\mathcal{S} = \{1, 2, 3 \dots S\}$ and $\mathcal{B} = \{1, 2, 3 \dots B\}$ denote the sets of sellers and buyers, respectively, where S is the total number of sellers and B the total number of buyers in the system. Each seller $i \in \mathcal{S}$ has a maximum amount of energy a_s^i kWh he is willing to sell. Each buyer $j \in \mathcal{B}$ needs a fixed amount of energy a_b^j in order to satisfy his local demand.

In order to balance the load among multiple sellers and ensure that no seller is overloaded, we adopt an increasing and convex cost function $C(L(i))$ that depends on the total load $L(i)$ per seller i . It represents energy cost in terms of cents per kWh.

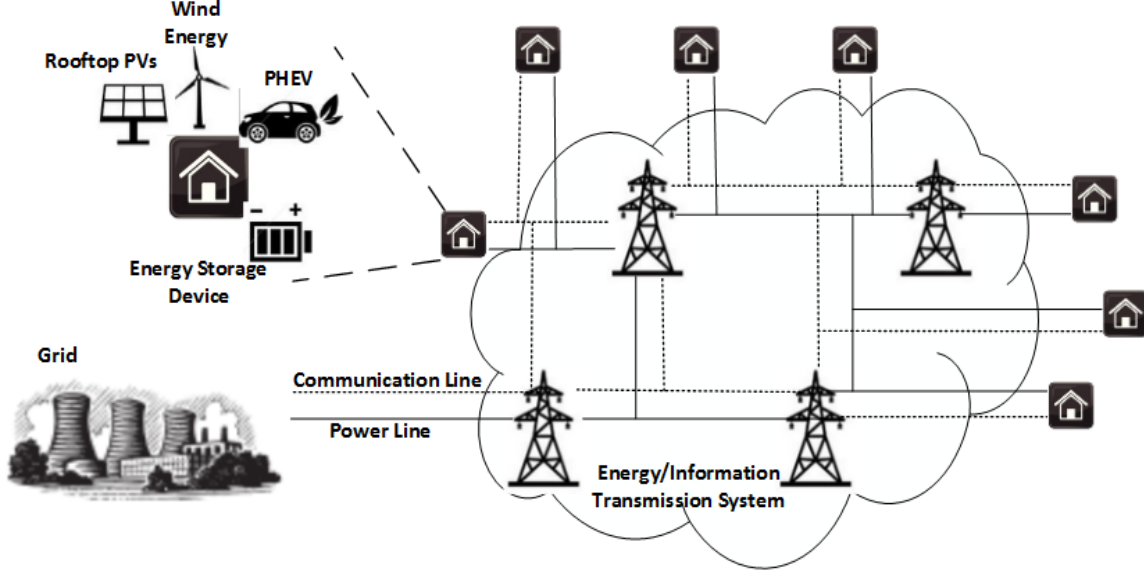


Figure 5.1: Smart Grid Neighborhood Architecture

$$C(L(i)) = Up^i \times L(i). \quad (5.1)$$

where Up^i is the wholesale energy price of seller i . Note that each seller specifies his wholesale energy price. We assume that the main electric grid is also a seller with higher wholesale energy price Up^g such that $Up^g > Up^i, \forall i \in \mathcal{S}$.

To model the smart grid infrastructure in Figure 5.1, we consider the set of transmitters $\mathcal{T} = \{1, 2, 3 \dots T\}$ where T is the total number of transmitters in the system. A transmitter can be connected to either a buyer, a seller, or another transmitter, all of which are generally referred to as nodes. It basically provides a way for energy and information to flow through the grid from one node to another. A Hop is defined as a single link between a buyer j and a transmitter t $H(j, t)$, a transmitter t and another transmitter t' $H(t, t')$, or a transmitter t and a seller i $H(t, i)$. A buyer j can reach a seller i through multiple paths $\mathcal{P}_{(j,i)} = \{P_{(j,i)}^1, P_{(j,i)}^2, P_{(j,i)}^3 \dots P_{(j,i)}^P\}$ where P is the total number of paths between j and i . A path $p \in \mathcal{P}_{(j,i)}$ basically consists of a set of hops $\mathcal{H}_p = \{H_p^1, H_p^2, H_p^3 \dots H_p^H\}$ that connect a buyer to a seller. We consider a set of hops \mathcal{H} that consists of all the hops in the system. Each hop H_p^h has a maximum capacity denoted as $H_p^h cap$ kWh, which represents the maximum amount of energy that can flow within this hop. A transmission cost, $H_p^h cost$

for every kWh of energy flowing, is also associated with every hop. It can be considered as tax imposed by the electric grid for using its infrastructure. We assume that the grid infrastructure is known to the buyers and that every buyer j can find all the paths to all sellers defined in the set $\mathcal{P}_{(j,i)}$. For instance, if we consider the grid infrastructure as a graph where the edges are the hops, and the vertices are the buyers, sellers and transmitters, then we can use a breadth-first search (BFS) algorithm to find all the paths from a buyer to all the sellers [154]. We assume that the communication is reliable such that both errors and delays are negligible.

5.3 Optimization Model

In this section we formulate an optimization problem that minimizes the total system cost. First, we calculate the energy bill for every buyer j , which depends on finding the amount of energy X_p passing through every path $p \in \mathcal{P}_{(j,i)}$ to get from each seller $i \in \mathcal{S}$.

The energy bill associated with buyer j is:

$$Bill(j) = \sum_{i=1}^S \sum_{p=1}^P X_{P_{(j,i)}^p} \times \left[C(L(i)) + \sum_{h=1}^H H_p^h cost \right]. \quad (5.2)$$

The energy bill $Bill(j)$ of each buyer j can be divided into two parts. For every seller $i \in \mathcal{S}$, we first consider the energy cost, which is defined as the amount of energy provided by seller i across all paths between seller i and buyer j times the seller's energy cost. Second is the transmission cost that is calculated by multiplying the amount of energy provided by seller i across path p and the transmission cost of this path, which is the sum of the transmission costs of the hops making up this path.

The goal of the centralized approach is to trade energy between buyers and sellers in order to minimize the total system cost that the total system energy bill. More precisely, for every buyer j , the optimization model finds the amount of energy X_p passing through every path $p \in \mathcal{P}_{(j,i)}$ to every seller i , which leads to the lowest system bill. The optimization

problem is defined as follows:

$$\mathbf{minimize} \sum_{j=1}^B \text{Bill}(j). \quad (5.3a)$$

subj.to

$$X_{P_{(j,i)}^p} = [0, a_s^i] \mid X_{P_{(j,i)}^p} \in \mathbb{N}, \forall j \in \mathcal{B}, \forall i \in \mathcal{S}, \forall p \in \mathcal{P}_{(j,i)}. \quad (5.3b)$$

$$\sum_{i=1}^S \sum_{p=1}^P X_{P_{(j,i)}^p} = a_b^j, \forall j \in \mathcal{B}. \quad (5.3c)$$

$$\sum_{j=1}^B \sum_{p=1}^P X_{P_{(j,i)}^p} \leq a_s^i, \forall i \in \mathcal{S}. \quad (5.3d)$$

$$\sum_{j=1}^B \sum_{i=1}^S \sum_{p=1}^P X_{P_{(j,i)}^p} \leq H_p^h \text{cap} \mid \mathcal{H}_p \ni H_p^h, \forall H_p^h \in \mathcal{H}. \quad (5.3e)$$

The problem in (5.3a) is modeled as an integer programming problem. Constraint (5.3b) ensures that each buyer j can not buy from a seller i more than the maximum amount of energy a_s^i offered by the seller i through every path $p \in \mathcal{P}_{(j,i)}$, where $X_{P_{(j,i)}^p}$ is the decision variable of the optimization problem. Constraint (5.3c) assures that each buyer j will get exactly its needed energy a_b^j from all the sellers through all the paths. Constraint (5.3d) ensures that each seller i can not trade more than its maximum amount of energy a_s^i with the buyers through all paths. Constraint (5.3e) limits the energy flowing in every hop in the system to its maximum capacity.

5.4 Energy Trading Game Theoretic Approach

The optimization problem described in the previous section can be solved in a centralized way to find the optimal solution for a given configuration of buyers and sellers. However, it is more beneficial to formulate a decentralized approach that can adapt to changes in the system and scales better. In this section, we formulate a non-cooperative game between the buyers, then propose a distributed way to solve the energy trading problem.

5.4.1 Energy Trading Game Model

The proposed decentralized game requires the participation of all the buyers and sellers willing to trade energy between each others. It consists of interactions across the sellers and buyers that happen during multiple stages. We consider players as the buyers in the set \mathcal{B} willing to buy energy from the set of sellers \mathcal{S} . Each player j has an energy trading vector $X(j) = [X_{P_{(j,i)}^1}, X_{P_{(j,i)}^2}, \dots, X_{P_{(j,i)}^P}]$, where $X_{P_{(j,i)}^p}$ is the amount of energy that will be bought from each seller $i \in \mathcal{S}$ through every path $p \in \mathcal{P}(j, i)$. The ultimate goal of each buyer is to select the energy trading vector that maximizes its payoff. In other words, each buyer chooses the amount of energy to buy from each seller through each path that minimizes its energy bill. This decision not only depends on the buyer's choices, but is also influenced by other buyers' choices. We assume that each player knows the set of sellers in the system, their offered energy and prices, as well as the infrastructure settings (hop capacity and transmission cost) before the game starts.

The payoff received by player j is defined as follows:

$$P^j \left(X(j), X(-j) \right) = -\text{Bill}(j). \quad (5.4)$$

where $X(j)$ represents the energy trading vector selected by player j and $X(-j)$ the energy trading vectors selected by all other players other than j . Buyers try to select the amount of energy that will be bought from each seller through each of the paths in order to maximize their payoffs. In order to minimize the energy bill, buyers should choose sellers that offer energy at a low price but at the same time these sellers should not be overloaded since the seller's energy price increases as its load increases. On the other side, the buyers' energy bill is affected by the number of hops as well as the transmission cost associated with each hop. Buyers should therefore choose paths that contain less hops at cheaper transmission costs.

5.4.2 Energy Trading Algorithm

We propose a repeated game that is played in a number of iterations. During each iteration, player j chooses the amount of energy to buy from each seller through each path or his

energy trading vector $X(j)$ for each seller $i \in \mathcal{S}$, which will maximize its payoff. Considering any player $j \in \mathcal{B}$ and assuming all the other players fix the amount of energy they buy from each seller through every path according to $X(-j)$, then player j 's best response can be calculated by solving the local optimization problem:

$$\underset{\forall X_{P^p}^{(j,i)} \in X(j)}{\mathbf{maximize}} P^j(X(j), X(-j)). \quad (5.5)$$

The optimization problem (5.5) is equivalent to the optimization problem (5.3a) but for one user since maximizing the payoff is the same as minimizing the bill. Therefore, each player $j \in \mathcal{B}$ will solve the optimization problem (5.6a)

$$\underset{\forall X_{P^p}^{(j,i)} \in X(j)}{\mathbf{minimize}} \text{Bill}(j). \quad (5.6a)$$

subj.to

$$X_{P^p}^{(j,i)} = [0, x^p] \mid X_{P^p}^{(j,i)} \in X(j), \forall i \in \mathcal{S}. \quad (5.6b)$$

where x^p is the minimum between x_s^i and the minimum of $x_p^h \forall H_p^h \in \mathcal{H}_p$, as defined below.

$$\sum_{p=1}^P X_{P^p}^{(j,i)} \leq x_s^i, \forall i \in \mathcal{S}. \quad (5.6c)$$

where x_s^i is the maximum between the remaining energy and fair share of seller i .

$$\sum_{i=1}^S \sum_{p=1}^P X_{P^p}^{(j,i)} \leq x_p^h, \mid \mathcal{H}_p \ni H_p^h, \forall H_p^h \in \mathcal{H}_p. \quad (5.6d)$$

where x_p^h is the maximum between the remaining energy and fair share of hop H_p^h .

$$\sum_{i=1}^S \sum_{p=1}^P X_{P^p}^{(j,i)} = a_b^j. \quad (5.6e)$$

Problem (5.6a) is referred to as a local optimization problem since it has only local variables for every player. Player j needs the energy trading vectors of all the other players as well as the cost function used by each seller. To ensure fair access to energy resources

between all the buyers in the system, every buyer can only buy his fair share of energy from each seller and he is allowed to pass only his fair share of energy within each hop. More precisely, within each seller i the fair share of a given buyer j is the offered energy a_s^i divided by the number of buyers willing to buy from this seller. The same applies for each hop considering the capacity of each hop that is divided by the number of buyers using it to get the fair share of a given buyer j . Constraint (5.6b) ensures that the decision variable is updated after receiving the energy trading vectors of other players. It limits the energy flowing in each path between buyer j and every seller i to the allowed energy x^p which is constrained by both the path and the seller. First, the maximum energy a buyer can receive through a path is constrained by the minimum energy allowed to flow through all the hops in that path. The hop constraint in (5.6d) ensures that the energy flowing in each hop is less than x_p^h , the maximum between the remaining energy and the fair share of this hop. Therefore, the sum of energy flowing through all the paths sharing the same hop is limited by x_p^h for every hop in the system. Every buyer can use the remaining capacity of the hop if it is underused, i.e. his fair share is less than the remaining capacity. For the sellers constraint, defined in (5.6c), the energy that a buyer j will get from each seller i is limited to the maximum between his fair share and the remaining energy at the level of this seller. At a given time, if a seller has only a few buyers that are willing to trade energy with him and still have considerable energy to sell; the next buyer can get the remaining available energy at the level of this seller even though it is bigger than his fair share. Finally, (5.6e) ensures that the amount of energy that a buyer j gets from all the sellers through all the paths is equal to his requested energy.

Algorithm 4 illustrates the proposed distributed algorithm. Initially, every buyer requests all his needed energy from the grid, which is considered as a seller with a higher energy price, and broadcasts a message containing his energy trading vector. These steps are done by all the buyers in order to initialize their energy trading vectors. Then, every buyer will execute the loop in lines 1 to 11 until no buyer announces a new energy trading vector. To avoid given advantages to any player, players run the algorithm at random time intervals. Inside the loop, as shown in line 3, each player will solve the local optimization problem (5.6a). That is, the player simply plays its best response as previously discussed.

If the current energy trading vector is different than the previous one, then, as shown in lines 5 and 6, the player updates its $X(j)$ and broadcasts a message containing his new energy trading vector. In this context, a player also updates $X(-j)$ once he receives a message from other players. The game is repeated until no player changes its energy trading vector, this happens when the algorithm converges and the equilibrium is reached. At this point, all players have locked in their energy trading vectors and decided not to change them as no more bill saving will be achieved.

5.4.3 Convergence

Nash equilibrium (NE) can be defined as a state of the game where no player can increase its payoff by unilaterally deviating from this equilibrium state. Before we can prove that the proposed distributed algorithm converges to a NE, we need first to prove the existence of such NE. According to [155], the existence of NE depends on a payoff function that is continuous when we have a compact action space for every player $j \in \mathcal{B}$ as in our case (ie. the energy trading vector $X(j)$ is bounded and closed since $X^i(j) \in [0, a_s^i]$ for every $i \in \mathcal{S}$). Therefore the NE exists in our case since the payoff function in (5.4) is continuous.

Every player $j \in \mathcal{B}$ plays his best response by solving the local optimization problem (5.5). As the players play the game, using Algorithm 4, in an asynchronous fashion the energy bill either decreases or remains unchanged whenever a player changes its energy trading vector. Since the energy cost is bounded below (always positive), the convergence to a certain fixed point is obvious. Once the fixed point of Algorithm 4 is reached, no player is able to improve its payoff by deviating from it when playing its best response. Therefore, the fixed point is the NE of the proposed game.

Algorithm 4 Algorithm for every Player $j \in \mathcal{B}$

Input: Set of S Sellers \mathcal{S} , their capacity, energy price, grid infrastructure .**Output:** The $X(j)$ for player j .Initially: Buy all the energy from the grid to initialize $X(j)$. Broadcast a message containing $X(j)$ to other players.

```
1: repeat
2:   At random instance of times Do
3:     Solve local optimization problem (5.6a)
4:     if  $X(j)$  changes compared to current energy trading vector then
5:       Update  $X(j)$  based on the new solution.
6:       Broadcast a message containing  $X(j)$  to other players.
7:     end if
8:     if an energy trading vector is received then
9:       Update  $X(-j)$  accordingly.
10:    end if
11: until no player sends any new energy trading vector
```

5.5 Performance Evaluation

5.5.1 Simulation Settings

The performance of the proposed energy trading algorithm is evaluated with a simulator written in Java using the CPLEX Java API [156]. For the purpose of the study, each seller has a random maximum energy in the range [10 – 100] kWh, while each buyer requests a random amount of energy in the range [10 – 50] kWh, according to a uniform distribution. We also consider that each seller chooses a unit price for trading energy between [0.05–0.09] cents per kWh according to a uniform distribution. The main electric grid is assumed to be a seller with unlimited energy and a higher price Up^g , which we set to 0.14 cents per kWh. The chosen prices are set in order to give artificial cost rates for simulation purposes only. For the electric grid infrastructure, we increase the number of transmission nodes as a function of the total number of buyers and sellers. For simplicity purposes, we assume

that the transmission cost and the capacity are the same for all hops in system and we set them to 0.04 cents per kWh and 1000 kWh, respectively. We also connect every buyer to the main electric grid through a hop with unlimited capacity. To assess the behavior of the proposed algorithm in different situations, we run multiple simulations with different settings. We first fix both the number of sellers and buyers in order to calculate the achieved energy bill for both the proposed approach and the centralized optimization. We then change both the percentage of sellers and the number of users in order to study their effect on the performance of the proposed algorithm. Finally, in order to study the fairness of the proposed algorithm, we set the same settings for all the buyers in the system, and then study the difference in the buyers' cost in the proposed algorithm and a modified version that does not implement fairness.

5.5.2 Simulation Results

In this section, the proposed algorithm is evaluated in terms of the following:

- **Energy bill:** represents the individual buyer's energy bill as calculated in equation (5.2).
- **System cost:** represents the system bill. It is calculated as the sum of the individual buyers' energy bills.
- **Equilibrium:** represents the average number of iterations it takes the proposed algorithm to stabilize. This happens when all buyers decide to not change their energy trading vector and no buyer sends a new energy trading vector. At this point, the game stops and equilibrium is achieved.
- **Fairness:** a fair algorithm treats the same buyers in the same way. This means that if two buyers have the same exact settings (energy required, connected to the same sellers through the same paths and hops), they should both pay the same energy bill. We use these settings in the last scenario and compare the buyers' energy bills in order to assess the fairness of the proposed algorithm.

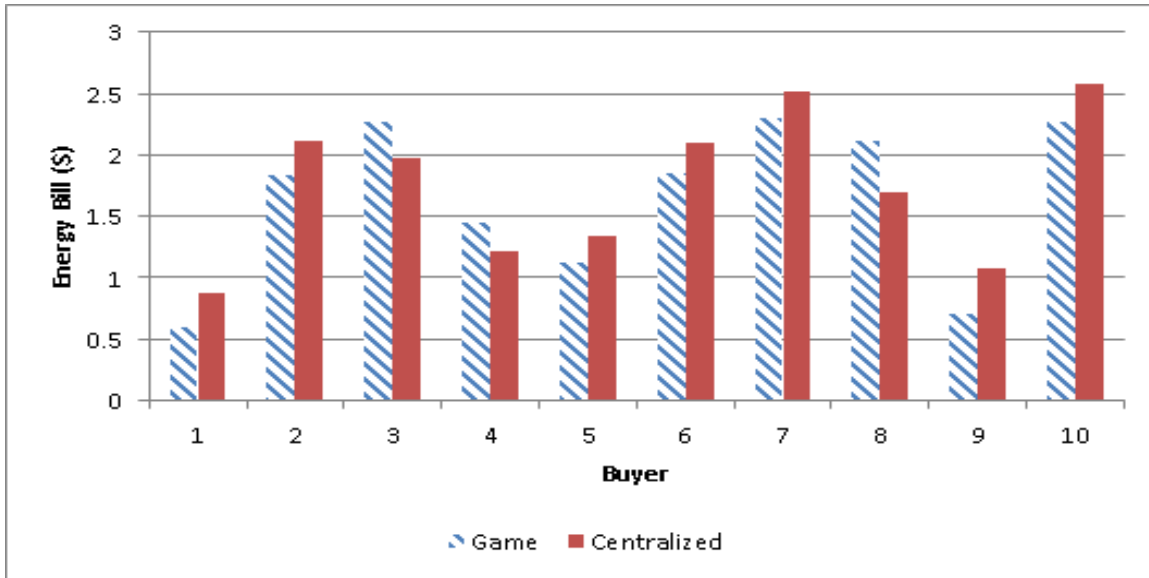


Figure 5.2: Energy Bill per Buyer

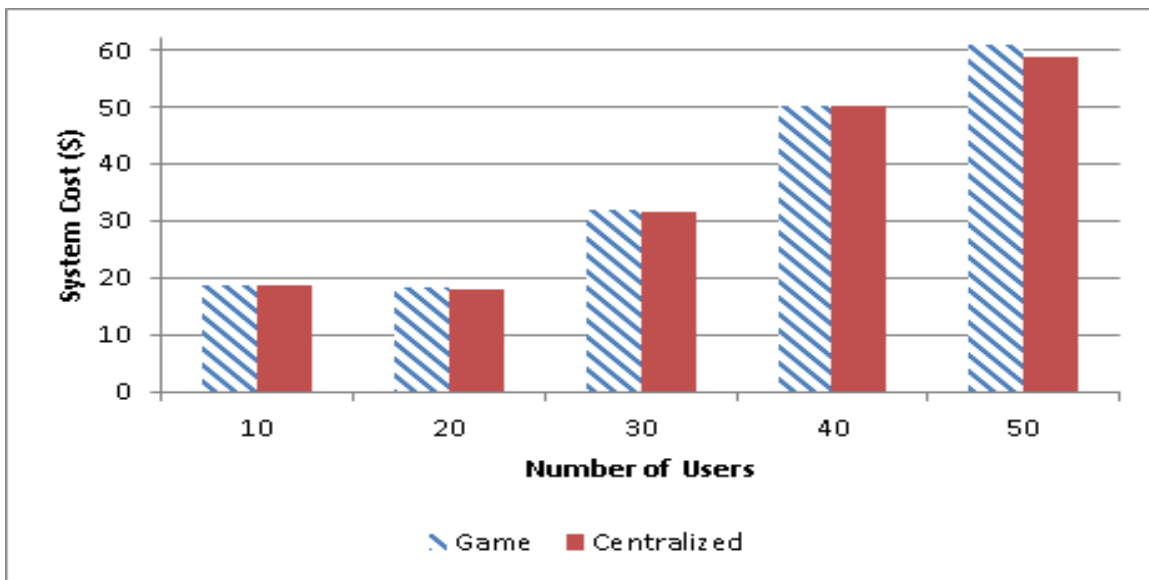


Figure 5.3: System Cost vs Number of Users

In the first scenario, we consider 50 users 30% of which are sellers and the remaining 70% are buyers. Figure 5.2 compares the individual energy bills of the buyers using the centralized solution and the proposed algorithm. Only a subset of users (10) is shown in the figure for illustration purposes only. We see that the difference in the energy bill of the proposed algorithm and the centralized approach is very small for all the users. We

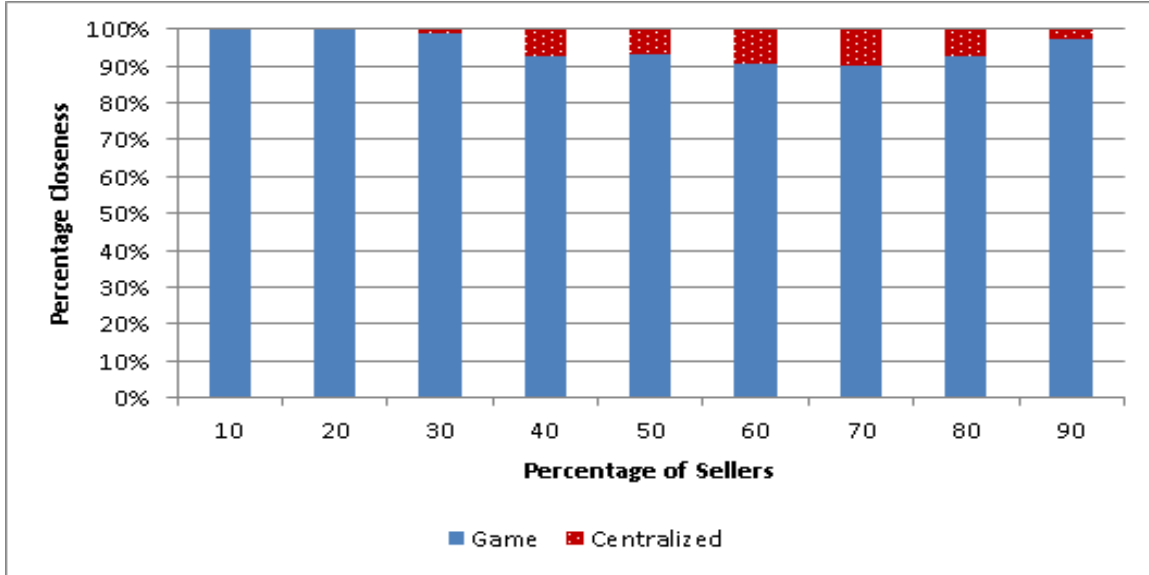


Figure 5.4: System Cost vs Percentage of Sellers

also notice that the individual energy bill achieved using the optimal solution is higher for some buyers and lower for others compared to the proposed algorithm. For instance, buyer 7 pays a higher bill using the centralized solution while buyer 8 pays a higher one using the proposed algorithm. In the centralized solution, the objective is to minimize the total system cost; therefore, some buyers can end up saving on their energy bill at the expense of others. In particular, a buyer might have to pay more if this will minimize the overall system cost. However, in the proposed game, each buyer strives to minimize its own energy bill but he is limited to his fair share, which is impacted by the decision of other buyers. This explains the slight differences in the energy bill between the centralized solution and the proposed game. A better comparison between the optimal solution and the proposed game is provided using the system cost metric as shown in the next figure.

In Figure 5.3, we change the number of users in the system from 10 to 50 and keep the percentage of sellers 30% in order to study the effect of the number of users on the total system cost. We see that the proposed algorithm achieves results that are very close to the centralized solution. In fact, the difference is negligible even if the number of users is increased. This proves that the energy trading algorithm also minimizes the total system cost by considering the individual energy bills of each buyer. In Figure 5.4, we fix the

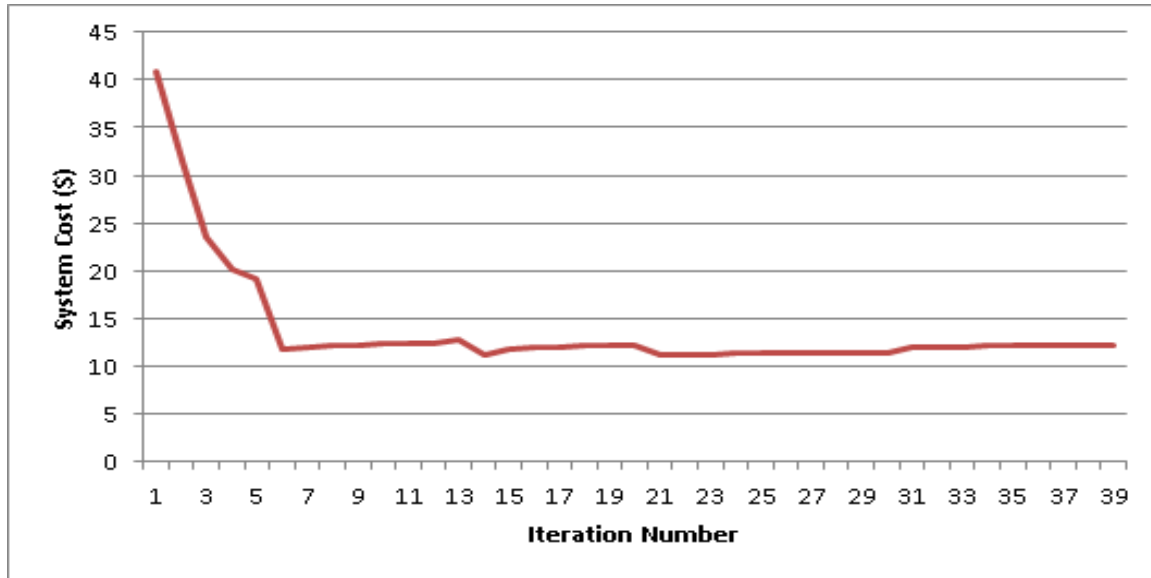


Figure 5.5: System Cost Per Iteration

total number of users in the system to 30 and increase the percentage of sellers from 10% to 90%. This figure shows how the system cost changes in function of the percentage of sellers using both the proposed game and the centralized solution. We see that the system cost achieved under the proposed game is 90% to 100% close to that of the centralized solution. Therefore, the proposed distributed algorithm achieves results that are close to the centralized optimal solution regardless of the number of users or the percentage of sellers/buyers in the system. Note that the slight difference in the system cost between the centralized approach and the proposed game is due to the fact that the centralized approach minimizes the system cost without taking into consideration how the individual users' bills are impacted. The notion of fairness is nonexistent. In the proposed algorithm, however, each users minimizes its own energy bill and has no concerns on how his decisions affect other users or the overall system bill.

We then simulate a scenario of 10 users only, where 30% of them are seller, in order to illustrate the trends of the resulting system cost. Figure 5.5 draws the changes in the system energy cost while the proposed algorithm proceeds along its distributed iterations. We clearly see that as users run the proposed algorithm, the total system cost keeps decreasing with each iteration until the algorithm converges after 30 iterations only, an

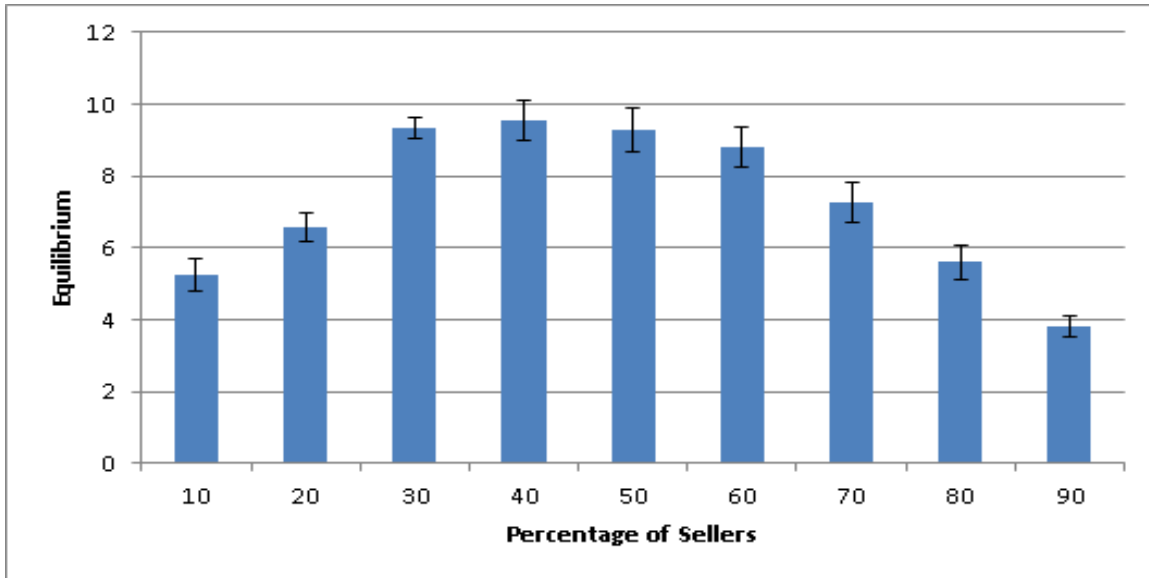


Figure 5.6: Equilibrium vs Percentage of Sellers

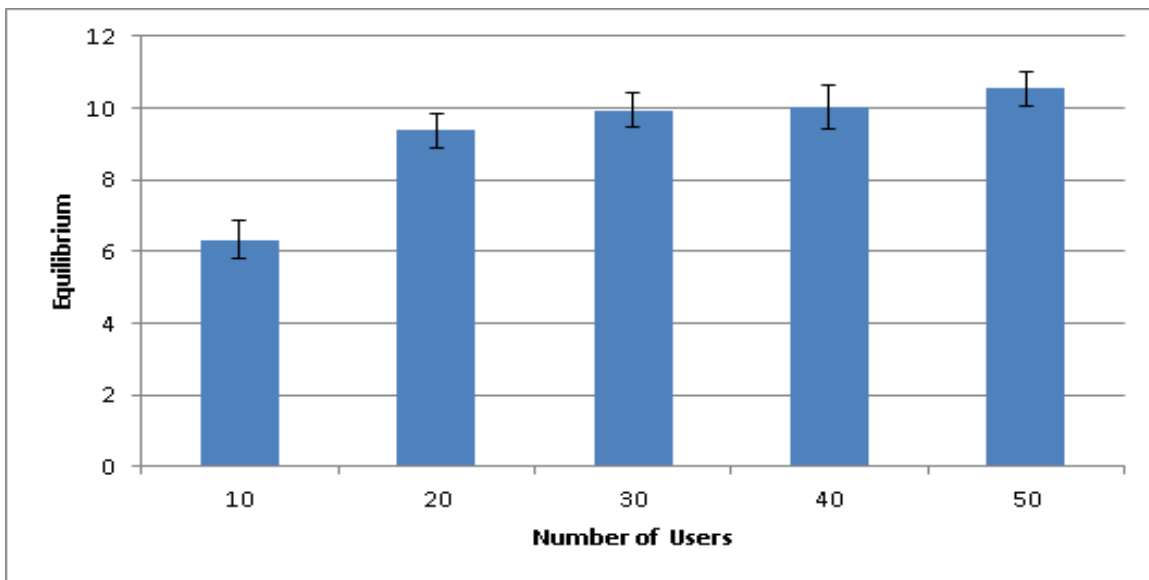


Figure 5.7: Equilibrium vs Number of Users

average of 4 iterations per user.

In the next two simulations, every simulation is repeated 30 times and the 95% confidence interval is reported. To study the scalability and the convergence of the proposed algorithm under different setting, both Figures 5.6 and 5.7 draw the equilibrium time vs different percentage of sellers and number of users respectively.

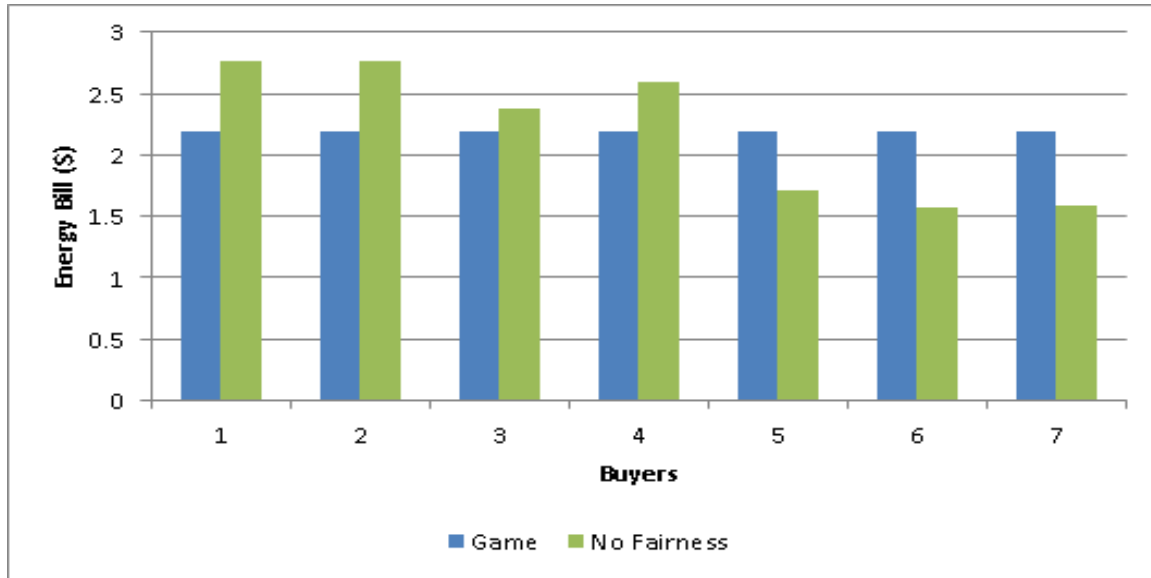


Figure 5.8: Fairness

In Figure 5.6, the total number of users is fixed to 30. First, we see that the equilibrium time varies in function of the percentage of seller. In particular, it starts from 5 rounds in the case of 10% of sellers, increases to 10 for 40% of sellers, and decreases again to 4 rounds for 90% of sellers. When the percentage of sellers is small, there are more buyers in the system but very few sellers. In this case, the best solution is to fairly share the available resources between all the buyers. Therefore, as each buyer solves its local optimization problem, it will only take a few iterations for each buyer to choose its own fair share of the available resources. However, as the number of sellers increases, buyers will have more resources to choose from, which raises the equilibrium time. Lastly, as the percentage of sellers keeps increasing to a very high level, making a scenario with very few buyers but a high number of available resources. Therefore, it is very unlikely that any two buyers will end up competing for resources. Hence, the number of iterations will be small. Still, overall the maximum number of iterations is capped to 10 iteration per user.

In Figure 5.7, the percentage of sellers is fixed to 30% while the number of users in the system is increased from 10 to 50. We see that it only takes a maximum of 10 iterations per user for the algorithm to converge even if we increase the number of users in the system.

To study the fairness of the proposed algorithm, we simulate a system of 7 buyers and 3 sellers, where all the buyers have been setup to have identical needs and paths to the other sellers. We simulate this scenario since a fair algorithm would charge buyers with similar needs and settings the same bill. We then solve the energy trading problem using the proposed algorithm and a variation of this algorithm labeled as 'No fairness'. This variation does not implement the fact that users can share the resources (seller's energy and hop capacity) fairly. In other words, if a buyer broadcasts its energy trading vector using the full capacity of a given seller, other subsequent buyers playing the game cannot share that particular seller's capacity. Energy is allocated on a first come first served basis. Figure 5.8 draws the individual energy bill for each buyer. We clearly see from the results that the proposed algorithm is fair as the final energy bills of all the buyers are exactly the same. In the 'No Fairness' variant, some buyers have a low energy bill at the expense of other buyers.

5.6 Conclusion

In this chapter, we proposed both a centralized and a distributed energy trading algorithm based on game theory, where buyers can buy extra stored energy from nearby sellers at a lower price. Buyers minimize their energy bill by selecting the best sellers in terms of cost, taking into account different constraints imposed by the grid infrastructure; namely energy transmission costs and the transmission lines' and sellers' capacities. First, we formulate the energy trading problem as a centralized optimization problem and then propose an algorithm to solve it in a distributed way. Using extensive simulations, we compared both the system total cost as well individual buyer's bills. The difference between the proposed algorithm and the optimal solution is negligible. We Also study the convergence time of the proposed algorithm and find that it takes very few iterations per buyer for the algorithm to converge. Finally, we show that the proposed algorithm offers fairness to its users by billing the identical users at the same price.

Chapter 6

Conclusion and Future Work

6.1 Concluding Remarks

The smart grid is an innovation to the traditional electric grid that is planned to solve its major drawbacks. Its emergence was driven by different factors such as the introduction of a high number of electric vehicles into the market as a cheap and clean alternative to oil. In addition, the increasing number of residential appliances has put more and more stress on the traditional electric grid [157]. One of the main applications of the smart grid is demand response, a scheme used to efficiently manage the energy usage across the grid in order to achieve different goals. Demand response benefits both electric utilities and consumers. For instance, it allows users to reduce their monthly energy bills by wisely choosing their energy consumption patterns. It also allows the utility to match the supply to the demand without the need for upgrading the existing electric infrastructure. In addition, it helps reducing the number of generated blackouts by flattening and balancing the energy consumption load across different periods of the day.

In this thesis, we have addressed the problem of load management in order to promote energy saving using the advanced functionalities of the smart grid. We proposed novel solutions, namely: user-aware demand management, fair billing within demand response in the microgrid, and energy trading in the smart grid.

First, we proposed a novel game theoretic demand management algorithm based on a modified regret matching procedure. The main goal is to balance the overall residential loads which maximizes consumers’ savings while preserving their comfort and preferences. The fundamental difference between the proposed algorithm and existing demand management mechanisms is its ability to allow its users to choose between prioritizing comfort over savings, or balancing the two. The proposed model also takes into consideration different types of appliances (hard, soft-consecutive/non-consecutive). To evaluate the proposed algorithm, we performed extensive simulations. The results show that the proposed algorithm efficiently distributes the load, and allows users to minimize their electricity bills compared to uncontrolled energy consumptions. In addition, we have analyzed the performance of the algorithm under different scenarios where we vary the type, number of appliances, and the proposed weighting factor that allows users to choose comfort or savings. Results also show the proposed algorithm converges in reasonable times and provides significant savings. Finally, we compared the proposed algorithm to an optimal centralized approach, and results show that it gets up to 96% closer to the optimal solution.

Second, we consider a microgrid scenario with local renewable and non-renewable resources that are shared amongst its users. The local resources are cheaper than external resources, which are only used when local demand exceeds local supply. In this context, the problem of sharing common resources within the microgrid in a fair manner is introduced. First, we introduce the concept of fairness and scope it within the problem of demand response in the microgrid. In order to divide the costs of using the shared microgrid resources in a fair manner between users participating in the demand response program, we propose the use of the Shapely value. Because of the limitations of calculating the Shapely value for a high number of users, we use a sampling based approach that runs in polynomial time to approximate the Shapely value. ApproShapley is used within the proposed demand response algorithm to assist users in making better decisions concerning shifting their energy consumption schedules, by sending them price signals. Simulations performed to evaluate the proposed algorithm show that using an approximation of Shapely value achieves better savings, helps flattening the load, and avoids peaks and rebound peaks from happening in the system. As a result, the total system cost is reduced and users’ bills

minimized. The use of ApproShapley within our proposed algorithm is also compared to using a proportional billing mechanism. Simulation results show that the ApproShapley provides better incentives to users participating in the demand response program.

Third, we proposed a centralized energy trading algorithm as well as game theoretic novel distributed algorithm. The goal of energy trading in the smart grid is to allow users to buy energy from nearby neighbors with an excess, at a lower price. This allows buyers to minimize their energy bill by selecting the best sellers in terms of cost, taking into account different constraints imposed by the grid's physical infrastructure; namely energy transmission costs and the transmission lines' and sellers' capacities. First, the energy trading problem is formulated as a centralized optimization problem. Then, we propose an algorithm to solve it in a distributed way. To evaluate the proposed algorithms, we run extensive simulations and compare both the system total cost as well individual buyer's bills. Results illustrate negligible differences between the proposed distributed algorithm and the optimal solution. Moreover, the proposed distributed algorithm converges in very few iterations, which makes it suitable for the smart grid energy trading market. Finally, we study the fairness of the proposed distributed algorithm and show that it enforces fairness to its users by billing identical users at the same price.

6.2 Future Work

Demand response, fair billing, and energy trading in the smart grid are currently getting more research attention and being widely investigated. Based on the investigations and findings of this thesis, there are many research areas that can be considered for further future research, these can be summarized as follows:

- Smart grid communication system: The information communication system implemented in all simulations in this thesis was kept at a minimal level. We assumed perfect communication with negligible delays and errors. The effects of errors, delays, and failures in the smart grid communication system might affect the operation of demand management schemes. Therefore, more investigations are needed to integrate

the communication aspect in the proposed algorithms in this thesis.

- Smart grid security: One of the major issues in the smart grid is the security of information being communicated among users, and with utility companies. The impact of security breaches on our proposed algorithms should be studied. Also, there is a need to examine how securing the smart grid using different techniques could affect the proposed algorithms. For instance, what happens if hacker commands appliances to falsify the information exchanged within the proposed solutions. In addition to securing data communication, there is a need for authentication and authorization schemes within the smart grid to ensure that users are truthful and take responsibility for their actions.
- The effect of malicious users: the proposed algorithms and solutions in this thesis assumed that users are willing to participate truthfully. Unfortunately, this assumption is not always valid in real-life scenarios. The effect of malicious users can be explored in the future and a solution that guards against malicious behavior is required.
- Smart grid resource discovery: We have assumed that the resources available within the smart grid, including distributed and renewable resources are known within the grid domain. However, in some cases, this resources may not be known. To the best of our knowledge, there is no algorithm or scheme that provides a list of available energy sources within a grid sub-domain. Further investigation of this issue and the study of how users can discover nearby energy resources in an efficient and scalable manner is needed. The dynamic nature of energy sources provided by users adds a layer of complexity to this problem and push towards efficient solutions that provide timely and accurate resource discovery. For instance, if the user spends too much time finding all the available resources and decides to use power coming from a wind turbine, this latter might become unavailable at the time of the users decision. Hence, it is very crucial that the discovery process be very accurate and take minimal time.

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List of Publications

- N. Yaagoubi and H. T. Mouftah, “Energy Trading in the Smart Grid: A Distributed Game Theoretic Approach,” *Accepted at Canadian Journal of Electrical and Computer Engineering*.
- N. Yaagoubi and H. T. Mouftah, “User-Aware Game Theoretic Approach for Demand Management,” *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 716–725, 2015.
- N. Yaagoubi and H. T. Mouftah, “A Distributed Game Theoretic Approach to Energy Trading in the Smart Grid,” *accepted at IEEE Electrical Power & Energy Conference (EPEC)*, IEEE, 2015.
- N. Yaagoubi and H. T. Mouftah, “Energy Trading in the Smart Grid: A Game Theoretic Approach,” in Proceedings of the *IEEE International Conference on Smart Energy Grid Engineering (SEGE)*, pp. 1–6, IEEE, 2015.
- N. Yaagoubi and H. T. Mouftah, “Fairness-Aware Game Theoretic Approach for Demand Response in Microgrids,” in Proceedings of the *Seventh Annual IEEE Green Technologies Conference (GreenTech)*, pp. 125–131, IEEE, 2015.
- N. Yaagoubi and H. Mouftah, “A Comfort Based Game Theoretic Approach for Load Management in the Smart Grid,” in Proceedings of the *IEEE Green Technologies Conference (GreenTech)*, pp. 35–41, 2013. **(Best Award Paper)**
- N. Yaagoubi and H. T. Mouftah, “A Game Theoretic Approach for Plug-in Hybrid Electrical Vehicle Load Management in the Smart Grid,” in Proceedings of the *IEEE Electrical Power & Energy Conference (EPEC)*, pp. 1–6, IEEE, 2013.

Appendix A

Smart Grid

A.1 Introduction

Traditionally, the crucial purposes of the electrical and distribution systems were successful delivery of energy and satisfaction of consumers demands. Grid reliability was basically achieved by having an excess capacity in the system where the electricity flows from central power plants to consumers. This way of operation was successful in the past since the energy production was reasonably cheap. However, as fuel cost rises and the climate changes, the stakeholders were pushed to invest more in finding new power-generation technologies [158]. In order to solve the problem of inefficient and unstable electric systems, which has resulted from the lack of interest in investing [159], the recent advances in Information and Communication Technologies (ICT) have initiated the vision of smart grid. In other words, the electric system is becoming smarter thanks to innovation and technology.

This appendix presents an overview of the definitions and semantics used in this thesis. It will also identify the context and scope of our work.

A.2 Traditional Electric Grid

It is worth defining and explaining the traditional electricity grid before clarifying the different features of the new smart grid. As illustrated in Figure A.1 [160], the electric grid is based on unidirectional broadcast infrastructure where the electricity flows from central power generators that are very high power AC plants operating at 50 or 60 Hz. The electricity is mainly generated using kinetic or electromechanical energy that are produced by the force of flowing water or heat engines fueled by chemical combustion or nuclear power. After that, the electric power is transmitted at high voltages through a large network of transmission cables in order to reduce the impact of loss in long distances. Once at the substation, the electric power is stepped down to the same level used in the distribution side and go into the distribution stage. At this last stage, the electric power is distributed to the various types of consumers and, depending on the needs of each side, the power is stepped down to the appropriate voltage. In this centralized existing grid, the only intelligence available is at central locations, which make the consumer's and distribution sides passives [161].

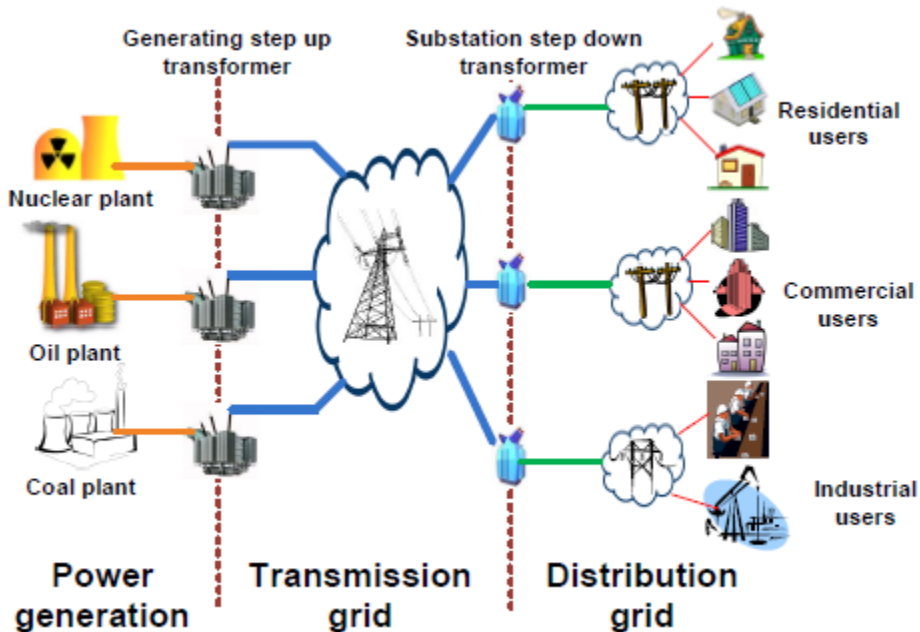


Figure A.1: Traditional Electric Grid

In the absence of communication between generation and consumption, the utility providers use some forecasting models, attained by gathering historical data in the past, in order to generate electricity. This generated electricity accounts for the customers demands in peak periods. The higher expenses needed to store the generated electricity might cause a great amount of energy to be wasted if the demands are lower than the peak. In fact, according to [162], 20% of the generation capacity of the electric grid is provided to meet peak demands while it is only needed 5% of the time. In addition to that, a loss of almost 8% can happen at the level of the transmission cables. In the case where the demands are higher than expected, some peaker plants can be used to satisfy the additional electricity. They generate electricity based on non-renewable resources, such as coal, for a period of few seconds up to few minutes [163]. Another weakness of the existing grid is caused by its hierarchical structure, which makes it exposed to domino-effect failures [162]. Moreover, as concerns over energy conservation and the environment arise, more countries are looking for ways to reduce the causes of global warming. In fact, it has been shown that almost 25% of global greenhouse gas emissions are caused by electric power, which pushes the grid utilities to think about changes to be considered in the future electric system [158]. This can be achieved by integrating renewable and distributed energy sources along the overall electric grid. Therefore, the traditional way of operation of the existing electric grid needs to be changed to enhance energy savings. In addition, the demands of energy are expected to increase as more electricity applications are being invented such as electric vehicles. This will put tremendous impact on the existing grid.

To face the above mentioned challenges, improve energy efficiency, reduce overall electricity consumption, integrate more distributed sources, and mitigate the consequences of climate change; the electrical grid needs to be significantly improved. The next generation electric grid is expected to be an intelligent system that is able to cope with the increasingly complex electric grid efficiently and to improve the grid reliability and utilization [158].

A.3 Smart Grid Definition

Smart Grid is an intelligent electric system based on modern information technologies. According to the National Institute of Standards and Technology (NIST), the smart grid is not yet defined in a detailed and comprehensive manner [164]. In general, the smart grid needs to incorporate the action of all users connected to it and provide utility companies with full visibility and ubiquitous control over their assets and services [162]. It also necessitates a complex two-way communication and electricity flows between intelligent components, advanced computing and information technologies, and business applications [161].

A.4 Smart Grid Systems

After defining the smart grid, we describe its different components. First of all, the NIST has presented a conceptual model, which is only a descriptive one to help promote understanding the smart grid operational domains. As shown in Figure A.2 [164], two way flow of information and electricity is supported in the smart grid. Communication is supported across all the smart grid components and electricity is no more unidirectional. In this model, the smart grid system is separated into seven domains, where each domain is grouping a set of systems, devices, buildings, organizations, and smart grid actors. All the elements of the domain share the same objectives and exchange information in order to accomplish specific goals. A detailed description of each domain and its sub-domains is provided in [164].

Various smart grid frameworks are being described in the literature depending on the focus of the research paper. For instance, the authors in [160] have divided the smart grid into three major systems: smart infrastructure, smart management, and smart protection systems. In this appendix, we will mainly describe the most important parameters that are significant to our research. For more information on the architecture and the various subsystems, the reader can look at [158], [160], and [161].

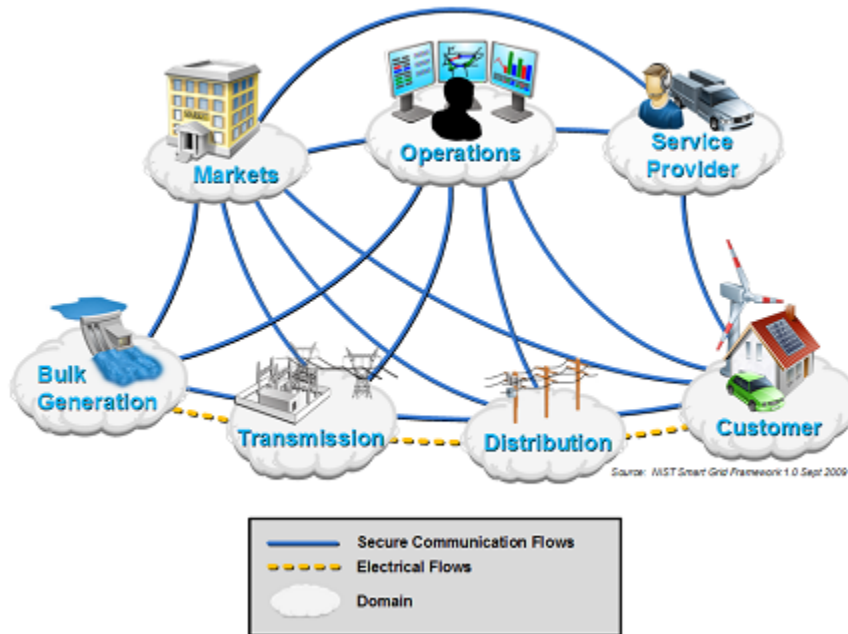


Figure A.2: Smart Grid Conceptual Model By NIST

A.4.1 Energy Sub-System

The energy subsystem is mainly a smart system that generates and delivers the electric power to the customers sides in a flexible and efficient way compared to the traditional way. In fact, more renewable energy sources are integrated as well as communication technology is used to promote energy saving and provide a balance between demand and supply.

Power Generation

According to [165], micro-generation devices are becoming more affordable lately. These devices are small energy generation equipment that usually produces power between 3 kW and 10,000 kW. They include rooftop solar panels, micro-turbines, wind power turbines, and fuel cells. The smart grid enables the use of these distributed energy resources across residential areas, this way consumers can produce portion or all of their required electricity in a cost effective way. The overall load on the electric grid can be also reduced, which improves the power quality and reliability. In addition, the two way flow of electricity

in the smart grid enables the users to put the energy generated by their own resources back into the grid. This new backward flow electricity is very beneficial since it helps balancing the loads by providing power to the grid when the demand is very high during peak hours [160]. The owner of these micro-generation devices can make profit as well by selling the energy to the utility companies. In contrast to the traditional electric grid, consumers are considered as an active component in the smart grid.

Transmission and Distribution

As the electricity demands are increasing worldwide, the need for an efficient and reliable transmission system is becoming an obligation for utility companies. First of all, the innovative technologies in power electronics as well as advanced digital technologies can be applied to face the aging infrastructure challenges and raise transmission performance to a higher level. In fact, utility companies are turning towards using various information technologies for the purpose of monitoring and controlling the electrical grid to improve the system security, reliability, and power utilization [165]. In addition, reliable communication and high transmission speeds are considered to be a significant key to a smarter transmission and distribution system. For instance, to prevent blackouts, the deployed technology needs to locate the problem and rapidly move this information between the transmission stations and control centers so that the appropriate action can be taken. As a result, all the advanced applications need to rely on an underlying reliable communication infrastructure [166]. The main purposes for the distribution side are delivering energy to the users in better way and serve their exact demands; therefore, multiple distributed generators will be integrated into the system. However, this new improvement will complicate the power control flow and pushes toward implementing an intelligent distribution system. Therefore, same as the transmission grid, advanced technologies are needed to improve the flexibility of flow control and increase the grid resilience and sustainability [160]. The exact applications and information techniques in the smart grid used will be explored later in the following sections.

A.4.2 Management Sub-System

The evolution of the smart grid does not only depend on the development of the physical infrastructure and power equipment of the electric grid but also on other aspects. It is true that to manage and control anything; data and information gathering need to be performed first. In Fact, within the smart grid, metering tools will generate different measurements to be used for grid management such as billing, grid status monitoring, and demands control.

According to [160], information metering and measurements can be divided into two categories: smart metering and measurements.

Smart Metering

The generation capacity, fuel prices, weather conditions, and users demands can all be considered as parameters that affect electricity price. During peak hours, the price is much higher than non-peak hours. In fact, non-peak prices at night are on average 50% less than those of the day [165]. Most customers choose to be charged using a flat rate for electricity even with the price fluctuations in wholesale markets. These customers will pay the same amount regardless of the demands that are put by customers on the electric grid or the time of use. One of the results of this charging scheme is that customers do not participate in energy savings since they do not receive any feedback from utility companies about any shortage of the supply [165]. Smart metering is introduced to resolve this situation by providing users with incentives to reduce their energy uses. It is used to permit utility companies to gather information from customers' devices as well as to give them the ability to select variable-rate pricing based on the time of day. In reality, the smart meters are similar to AMI meters, which are used in automatic metering infrastructure systems. AMI metering systems are built based on Automatic Meter Reading (AMR) systems, which permit automated meter readings where meters data are collected and transmitted to a central unit. The data gathered can be used for billing purposes as is the case of energy consumption data or for troubleshooting as is the case with diagnostic and status data [2]. In addition, the AMI system differs from the traditional AMR system by enabling two-way communications with the meter and reporting every hour or more frequently. Enhanced

system operations, power and demand management are achieved since all the gathered information is available in real time and on demand [24]. Smart meters are devices similar to AMI meters; they gather customers' energy consumption for each hour or less and send it back to the central utility for billing and monitoring purposes [24]. They also enable two-way communication between the meter and the central utility and they can control and manage the user's devices by plugging or unplugging them remotely depending on the loads and user's needs. Smart metering has many advantages from both customers' and utility perspective. For instance, the users can manage their energy consumption by shifting their appliances to low price periods since they can get the real cost of energy. From the utility side, better energy efficiency can be achieved with the feedback received from smart meters.

Smart Measurement

One of the purposes of the smart grid is increased system reliability which can be achieved with monitoring and measurement approaches. Sensors are low cost, low-power devices that communicate over short distances. They are being used for multiple monitoring and measuring purposes such as weather conditions, mechanical stress, and pressure [167]. For the smart grid, power cut can be avoided if the cause of the failure is detected and appropriate actions are taken right away. Installing sensors all over the electrical grid will monitor the mechanical and electrical status of transmission and distribution lines and will provide utility companies with a complete physical and electrical picture of the power system in near real time. As proposed by [168], the use of sensor networks will help in determining the appropriate control procedures to be executed once mechanical conditions appear in grid. Other measurement devices can also be used such as phasor measurement units, which are used to measure the electrical waves on the electric grid in order to determine system condition [160].

With the large amount of information gathered with the smart metering and monitoring, various information management approaches can be applied in the smart grid such as data modeling, information integration and optimization to improve information effective-

ness [160].

Applications

Advanced management applications are being established thanks to the improved information gathering and the enhanced physical infrastructure within the smart grid. The main objectives of the smart grid applications are focusing on enhancing energy efficiency, utility maximization, reducing electricity cost, and balancing the demand and supply. Potential applications can be assembled into three main categories according to their main objectives: customer side's applications, transmission and distribution side's applications, and supplier side's applications [161].

The first category is basically concerned with managing electricity consumption in homes, offices, and factories. By using various management programs, smart meters, smart building with smart appliance and energy dashboard, utility companies and consumers are able to improve the energy consumption as well as respond to the alterations in electricity demands more efficiently [165]. HEM system emphasizes on managing energy on the consumer side by controlling the various residential appliances in order to reach a balance between power supply and demands. HEM systems are composed of several integrated parts. Smart appliances are residential appliances equipped with communication and intelligence units so that they can be monitored in a remote manner. These appliances make users aware of their energy use which promotes an energy efficient and eco-friendly behavior [169]. According to [170], the HEM system can provide either informative, automated, advanced, or integrated functionalities. The informative services basically give users overviews about their exact energy consumption in different graphical forms. The automated ones provide the customer with the option to set different priorities to the domestic appliances.

AMI is considered as the key of the smart grid. It enables a two way communication between advanced meters or smart meters and the utility in order to monitor power usage. It integrates multiple sensors, monitoring systems, communication networks, and computer software. Therefore, it is considered as an enabling infrastructure that allows the imple-

mentation of multiple advanced management systems such as meter data management system which stores and processes metering data to generate information or messages to the customers including intelligent advice about their use of energy [171].

Another type of demand management supported by the smart grid is the demand response program. Within the traditional grid, utility companies try to match the supply of the generated energy to the demands by putting extra generating plants as backups in the case of sudden increase in energy demands. As previously described, this process is unpractical, expensive, and not possible in the near future due to depleting energy resources. Demand response refers to the mechanisms used by utility companies to manage end-user energy consumption in response to supply conditions [24]. As result, with the use of demand response programs utility companies are no more required to match the supply to the demands but instead match the demands to the available energy supply. This is achieved using different control strategies that encourage the customers to be active entities and change their energy consumption in response to changes in the electricity price [160]. The main purpose of these programs is to use the available energy in an efficient manner, improve system reliability, and achieve cheaper operation of the whole power systems.

Transmission and distribution management applications' are being used in the smart grid to monitor and control the electrical grid in real time. Based on monitoring techniques, blackouts can be avoided by determining and isolating the cause of power outage. Substation Automation System (SAS) is one of these techniques that emphasizes on substations. The substation is a switchyard facility in the electric grid that consists of multiple power equipments, such as transformers, switches, and circuit breakers, used mainly to transfer an incoming voltage into a higher or lower voltage [172]. SASs offer effective tools to monitor, collect, analyze data, and protect substations and their devices. A significant number of intelligent electronic devices such as sensors are installed within the substation.

Distribution Automation (DA) is another automation concept applied on the bridge between transmission systems and customer locations. The details of DA differ from one utility system to another but generally it is defined as the ability to use automation technologies in order to remotely monitor, control, manipulate, protect, and coordinate dis-

tribution components in real time or non-real-time modes [173]. The DA is considered to have an active role in the process of energy distribution, according to the US Smart Grid Market. The effect of an electrical cut is reduced as the DA achieves much faster fault correction [161]. An enhancement of the basic DA is advanced DA that provides new technological capabilities such as more widespread communication interface within the devices and advanced integrated and coordinated protection in order to attain intelligent fault location and faster auto-restoration [174].

A power cut might result from several reasons such as failures at a power station, destruction in the transmission and distribution lines, or a short circuit. Therefore, outage management, and restoration are very essential in any electrical system to protect and maintain the electricity transfer in the whole electrical grid. An Outage Management System (OMS) is composed of a set of technologies that can locate the cause of power cut, restore the supply of electricity by changing the direction of power transfer or by reconnecting the faulted line, and perform reliability reporting and outage prediction and analysis [175]. Outage management can be improved by using the advances of the smart grid. In fact, with the integration of AMI, an outage notification message can be sent from a smart meter to the OMS management server as soon as power cut is detected, before it even gets reported by the customer. Also, the OMS could utilize the data collected by smart sensors and fault location systems in order to determine an accurate scope of the electricity cut [173].

Wide Area Situational Awareness (WASA) Systems consist of a combination of technologies used to achieve an effective system monitoring and to provide a wide picture of the grid status in real time [176]. Generally, it is used to monitor the performance of the electric grid and its components in order to identify causes of failures and respond to them before the occurrence of disturbances.

The smart grid enables new generation techniques within the electrical grid, which pushes toward creating various type of application that integrate multiple parties.

The integration of distributed micro generation devices across residential areas is very beneficial to the electrical grid as they are the enabling agents of lower carbon footprint,

lower fuel use, and less power loss on the transmission and distribution lines [161]. However, it is very challenging to deploy renewable resources since they are subject to wide fluctuations [165]. For instance, as the weather conditions change, the sky becomes cloudy or the wind stops blowing, power generation will be suspended, which may cause energy deficiency in the grid. Therefore, it is necessary to deploy an effective scheme that is aware of the variable generation of these sources. For example, the smart grid needs to incorporate weather forecast reports and instantaneous output monitoring so that the utility companies can anticipate the electricity shortage in time and react to it by finding other resources. In addition, an advanced distributed storage can compensate for the non-consistent nature and the unexpected shortages of the distributed renewable resources. Various energy storage techniques are available but with the development of electric vehicles, new ways to store electricity are becoming available. The batteries in electric cars can be used to store energy from the distributed energy resources when the fluctuating supply of these sources can be matched to changing users demands. The operations that involve the use of electrical vehicles by the grid are entitled as vehicle to grid or V2G operations.

A.4.3 Communication Sub-System

The smart communication subsystem is essential to the operation of the smart grid. It is responsible for connecting different devices, systems and applications, and for transmitting information among them. Communication takes place at different levels in the smart grid. For instance, devices within a house or residential building communicate with a central controller to coordinate tasks such as energy usage. Within a micro-grid, communication is needed between different buildings and the central station. At the macro-grid level, different components of the smart grid such as generation and distribution stations communicate to coordinate energy transfer, usage and pricing. Therefore, the type of networking and communication technologies needed may differ depending on different factors. The debate on which technologies should be used in different domains of the smart grid is mainly due to the existence of different types of networks that must coexist and operate smoothly and seamlessly [160]. Before discussing how different communication technologies fit into the

smart grid communication subsystem, it is vital to state the different requirements and constraints that the smart grid puts on those systems.

Requirements and Challenges

Communication technology represents an enabling and essential component of the smart grid. However, the numerous components and heterogeneous devices making up the smart grid add a layer of complexity and challenges that must be addressed to build secure, robust and fully functional smart grid networks.

In the context of smart metering communications, we identify three types of networks: HAN, Neighborhood Area Network (NAN), and Wide Area Network (WAN). Each of these networks has typical communication requirements and can employ different technologies. Within each network, a HAN for example, different devices and meters can use different communication technologies. The HAN should support devices with different network interfaces. Wireless technologies represent one of the strong candidates in smart metering communications. However, their reliability and security pose challenges to their deployment in such scenarios. Moreover, the communication subsystem underlying a smart grid may experience unpredictable dynamic behavior such as topology changes.

A key feature of the smart grid is the interconnection of a large number of energy distribution networks, power generation sources and energy consumers. Each of these entities will have a varying number of components that need a way of communicating that is independent of the physical medium used, the manufacturers and the types of devices. Subsequently, multiple and different communication technologies and standards could coexist in different parts of the smart grid system. Interoperability is therefore crucial for proper operation of the different components of the smart grid. Standardization efforts for communications networks in the smart grid should focus on making interfaces, messages and information flows interoperable, rather than focusing on defining one specific technology.

The smart grid system must be scalable and provide efficient internetworking among the increasing number of cellular and local area networks. Although topics such as connection

and intelligent handover management have been widely explored, the characteristics of the smart grid metering and control traffic cannot be accurately predicted. As traffic will be heterogeneous and traverse different kinds of networks, interoperability is a key feature for successful smart grid deployment and operation.

In the light of these challenges, several communication protocols have been proposed for the smart grid communication subsystem. However, the heterogeneous and dynamic nature of smart grid networks makes the decision of choosing a specific technology difficult. A smart grid communication subsystem must satisfy a minimum basic number of requirements [177]:

- Quality of Service (QoS) support: the communication subsystem must support different classes of QoS to accommodate different types of data and control. For instance, critical data such as power failures must be delivered in a timely manner.
- Reliability: the communication subsystem must guarantee the reliability of its operation. Such task is not trivial in the presence of a large number of devices connected through different communication technologies.
- Availability and coverage: the communication subsystem must be highly available and cover large areas of the smart grid. This satisfies the principle that the smart grid is able to promptly respond to events occurring anywhere in the grid.
- Security and privacy: the communication subsystem must guarantee security and preserve privacy of all entities involved in the smart grid.

Wireless Technologies

Wireless technologies offer many advantages over wired technologies such as easy and rapid deployment, low installation costs, and mobility support. Wireless communication can be deployed anywhere and anytime. In the following, we briefly describe wireless communication and networking technologies that can be applied in future smart grid systems:

- **Wireless Mesh Network (WMN):** is a radio communication network of nodes organized in a mesh topology. Some of its advantages as smart grid communication subsystem include increased communication reliability and automatic connectivity, high data rate and large coverage. New specifications for WMNs are being actively developed by Industrial standards groups, such as IEEE802.11 and IEEE802.16.
- **Cellular Communication Systems:** are radio networks distributed over land areas called cells, each serviced by a fixed base station. Using existing 3G or 4G cellular technologies makes obtaining quick and cheap data communication coverage over large geographical areas rapid and easy. New standards are being developed to improve cellular communication systems QoS and to provide more bandwidth, high data rates, high reliability and low delays.
- **Cognitive Radio:** is designed to use the best available wireless channels in the surrounding area and is more likely to be used in the smart grid with unlicensed spectrum.
- **Wireless technologies based on 802.15.4:** three communication technologies have been recommended to be used in the smart grid communication subsystem [178]. These are ZigBee, ISA100.11a, and WirelessHART. ZigBee was designed for low data rate, long battery life, and secure networking applications. It is widely used in consumers' home networks. In fact, many electric utilities [162] and the NIST [164] have identified ZigBee and ZigBee Smart Energy Profile (SEP) as communication standards for use in the customer premise network domain of the smart grid [179]. On the other hand, WirelessHART uses a time synchronized, self-organizing, and self-healing mesh architecture using the IEEE802.15.4 standard in the 2.4 GHz radio band. ISA100.11a (Wireless Systems for Industrial Automation: Process Control and Related Applications) is an open wireless networking technology standard developed by the International Society of Automation.
- **Satellite Communications:** is a solution that provides rapid installation and global coverage, hence making it a good candidate for remote control and monitoring op-

erations. Satellite communications is a cost-effective solution for cases where no communication infrastructure already exists, such as remote substations and generation deployments; for example, those based on wind energy [180]. Moreover, satellite communications eliminate the risk of natural disasters or communication system failures of ground terrestrial-only architectures. In fact, satellite communications can be used to provide a backup to the terrestrial communication system in cases of disasters or failures. However, we identify two major drawbacks of satellite communications [181]. First, it experiences a considerably large delay than terrestrial communication systems, making protocols designed for terrestrial communications, such as Transmission Control Protocol (TCP), unsuitable for satellite communications. Second, satellite characteristics are unpredictable as they vary depending on weather conditions and the effect of fading which can significantly degrade their performance.

- **Free-Space Optical and Microwave Communications:** microwave technologies are used mainly for point-to-point communications and provide secure information transfer at high bandwidths thanks to the use of conveniently sized antennas to send their small wavelength. These optical wireless technologies not only provide long-distance point-to-point communication in rural or remote areas, but are also useful in dense urban areas where microwave solutions fail due to high interference [182]. Therefore, microwave or optical communications can be used to build a communication backhaul network for the smart grid when using other wired or wireless technologies is costly or impractical. However, their communication qualities are affected by obstacles and environmental limitations due to their need for a line of sight.

Wired Technologies

As opposed to wireless technologies, wired technologies provide many advantages such as high data rates and high reliability. However, they too suffer from many limitations such as high cost of deployment and inflexibility. We briefly outline two of the most important wired communication technologies with potential future in the smart grid.

- **Fiber-Optic Communications:** is widely deployed worldwide by telecom companies to connect their networks because it offers very high data rates and very low latency. Moreover, fiber optic communications has also been used by power companies to connect their network control facilities to the generation network. These networks are immune to both electromagnetic and radio interference which makes them ideal for use in high voltage environments. This technology represents a strong candidate for smart grid backbone networks thanks to its characteristics [181]. Although it is a fact that fiber optics is an expensive technology, it is believed that it is still a cost-effective solution for high speed communication backbones in the smart grid, since it is already widely deployed in today's networks with a large portion of unused spare capacity.
- **Power line Communications (PLC):** is a technology used to transmit data on a conductor that is primarily used to transmit electrical power. It has been used by some utility companies for remote metering and load applications [183]. However, the actual role of PLC in the smart grid is still an open issue. Compared to other technologies, PLC is the most cost-effective one since the infrastructure already exists. Yet, some researchers have expressed concerns on PLC mainly on security due to the nature of power lines [184] [185]. PLC uses power electronics, such as thyristor, to manipulate high-voltage waveforms and create a waveform disturbance such as voltage sag to transmit information and signals among applications.

A.4.4 Microgrids

A new concept that is stimulated by the integration of distributed generation in the smart grid is the Microgrid. With the availability of the distributed resources, any group of energy resources and loads can have their own local generation and consumption. This group is organized into the so called microgrids. They can be operating in a semi-autonomous way, where they are connected to the main electric system but in case of failures can be isolated and function on their own [176]. When the microgrids are working based on their own resources and without any supply for the main electrical grid, they constitute an islanded

microgrid [161]. The Microgrids help in reducing the energy wasted across the transmission and the distribution lines as less energy transfer is induced. In general, they enhance the energy efficiency and reliability of the electrical system as whole [176].

Microgrids are comprised of several basic technologies including distributed generation, distributed storage, interconnection switches, and control systems. One of the technical challenges is the design, acceptance, and availability of low-cost technologies for installing and using microgrids. Several technologies are under development to allow the safe interconnection and use of microgrids. Since the introduction of the Smart Grid system, research has been on-going for standardizing microgrid systems with regards to interconnection, microgrid controllers and information models.

A.5 Summary and Discussion

This chapter discussed background details of the smart grid including its general architecture and different components.

Appendix B

Game Theoretic Methods

Game theory is a formal analytical and conceptual framework of a set of mathematical tools used to study complex interactions between independent rational players. It has been widely used for several decades in different disciplines including economics, politics, psychology, and engineering [186]. The introduction of advanced technologies and services in the smart grid implies that game theoretic approaches will become important in the design and analysis of smart grid systems. Smart grid characteristics create a need for new models and algorithms for its communication and control. In particular, there is a need for distributed operation of smart grid nodes. The heterogeneous nature of the smart grid which is composed of micro-grids, appliances, smart meter...etc, and the need for integrating advanced techniques from other disciplines makes it more challenging to design and implement new techniques for smart grid control and operation. Finally, low-complexity algorithms are required to represent both collaborative and competitive scenarios between smart grid nodes. Game theory provides a robust framework that can address these and other challenge and provide efficient solutions to many smart grid issues.

The mathematical framework of game theory can be divided into two major parts: Noncooperative and Cooperative.

B.1 Noncooperative Game Theory

Noncooperative game theory is used to investigate and analyze the decision making processes of independent players (entities) which have either partially or totally conflicting goals over the outcome of the decision process, which is also affected by their actions. In particular, noncooperative games serve to capture a distributed decision making process which enables players to optimize their objective functions coupled in the actions of all players, without any form of communication or coordination. To this end, noncooperation does not necessarily imply that the involved parties, or players, do not cooperate. What it means is that any cooperation that happens must be self-enforcing with no communication of strategic choices between the parties.

Noncooperative games can be divided into two groups: static and dynamic games. In static games, the notion of time or information have no effect on the players' actions or choices. In a static setting, a noncooperative game is similar to a one-shot process where players take their actions only once, either simultaneously or at different points in time. On the other hand, players in dynamic games hold some information on each others' actions, can act more than once and time has a central role in the whole decision making process [187].

A static noncooperative game comprises of a set of players, the actions sets and the utility functions. The goal of each player is to choose the action that optimizes its utility function. The utility function does not only depend on the player's own action, but also on other players' actions. In a dynamic game, more components need to be defined. These include the information sets, time, or history of past actions usually reflected within the utility functions. In a static game, the notion of an action coincides with that of a strategy. In dynamic games, strategies are defined loosely as functions of the available information for each player. The strategies can be made either in a deterministic way (pure strategies), or by way of a probability distribution on the set of actions (mixed strategies). The goal of noncooperative game theory is to provide techniques and algorithms to solve such optimization problems and characterize their outcome, especially when cooperation (coordination and communication) is non-existent between the players.

Nash equilibrium is one of the most crucial solution concepts for game theory in general and noncooperative games in particular. It is a state where no player can improve its utility by changing unilaterally its strategy, given that all other players' strategies are fixed. Nash equilibrium has both advantages and drawbacks. For instance, it characterizes a stable state of the game where no player can improve its utility by unilaterally changing its action while other players fix their actions. Such state can be reached by players in a distributed way with little or no cooperation. However, a noncooperative game can have multiple Nash equilibria, and so selecting an efficient one can be challenging. Also, a Nash equilibrium is guaranteed to exist in mixed strategies only, even in finite games [188]. In order to provide convenient solutions for noncooperative games, other games theoretic techniques such as pricing are used to complement and extend the Nash equilibrium [187].

B.2 Cooperative Game Theory

While it is assumed in a noncooperative game that players cannot coordinate or communicate with each other, cooperative game theory is used in situations where players are allowed to communicate their actions. Cooperative game theory studies the case where players decide to actually cooperate and investigate how can incentives be used for independent decision makers to act together as a single entity and improve their position in the game. There are two parts of cooperative games: Nash bargaining and coalitional games. The former deals with cases where players need to agree on the terms under which they cooperate, while the latter deals with the formation of groups or coalitions. Basically, cooperative game theory provides tools to enable players decide the terms of cooperation and select whom to cooperate with under certain incentives and fairness rules [188].

B.3 Learning in Game Theory

The efficiency of equilibrium in game theory is an important aspect that allows players to reach a desired outcome in the game. However, to reach such equilibrium can be challenging

in some cases [189] [190] [140]. In fact, players must follow certain rules that allow them to make observations on the current game state and choose an action from their set of strategies. A learning scheme is a repetitive process that involves three steps performed by every player at each iteration [190]: First the player observes the environment and the current state of the game. Second, the player estimates the prospective utility, and third the player updates its strategy based on the observations made.

A number of learning algorithms have been proposed in the literature [189] [190] [191] [192] [140]. The following is a summary of some of the famous and widely used algorithms:

- Best response dynamics is one of the simplest learning algorithms. At each iteration, a player simply selects the strategy that maximizes its utility. This algorithm is simple to implement but suffers from some drawbacks. For instance, it is not guaranteed to converge to an equilibrium for all types of utility functions [191]. Moreover, it is highly sensitive to initial conditions and changes in these conditions may lead to different equilibria. Finally, using the best response approach does not guarantee convergence to an efficient equilibrium.
- Fictitious Play is another learning algorithm where each player, at each iteration, observes the actions of other players and computes the empirical frequency with which it chooses an action. Each player subsequently selects its optimal strategy in a given iteration given the empirical frequency estimation. Fictitious play is one of many special games known to converge to a Nash equilibrium [190].
- Regret matching, contrary to best response and fictitious play algorithms where players try to maximize their utility, is a type of learning algorithms where players try to minimize their regret of choosing a specific action. The regret being the difference in the utility of always playing a certain action, and the utility of playing the current action. More information can be found in [190] [191] and [192]

Other learning algorithms such as reinforcement learning or stochastic learning are also used in game theoretic approaches in order to achieve a desired system state [190].

Appendix C

Confidence Intervals

A Confidence Interval (CI) is a measure used to quantify uncertainty over a collected sample of data. It is defined as the estimated range of values within which a generated data lies with a specific probability. For instance, a probability of 95% implies a confidence of 95% that the collected data lies in a certain “confidence” interval. The Confidence Limits (CL) represent the end points of the confidence interval. The CL for a sample of data n that is normally distributed is computed as follows:

$$\mu \pm z \frac{\sigma}{\sqrt{n}} \quad (\text{C.1})$$

where μ is the mean of n , σ is the standard deviation of n , and z is the significance level. Equation C.1 implies that the CI is centered at the mean μ of the data gathered.

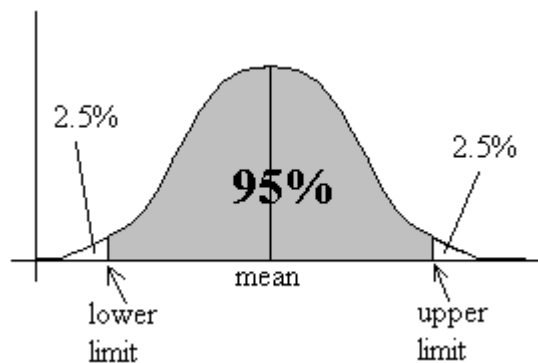


Figure C.1: The normal distribution function of sample data n with mean μ for computing the 95% CI

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990

Figure C.2: Snapshot of the z-table

The significance level z specifies the area under the normal distribution curve corresponding to the desired confidence interval as shown in Figure C.1. Hence, to compute the 95% CI for the normal distribution in Figure C.1, we exclude 5% of the area under the curve from the computation. 2.5% of the area on both sides of the mean μ is excluded to make for the total of 5%. The next step is to find the area corresponding to 95% of the sample of data n using the z-table. This is a table populated with difference values of z , areas, that correspond to different confident levels.

Given a probability $1 - \alpha$, we define the interval $[L(\mu), U(\mu)]$ such that the probability is given:

$$P[L(\mu) \leq \mu \leq U(\mu)] = 1 - \alpha \tag{C.2}$$

where α represents the significance level used to compute the confidence level. The confidence level equals $100 \times (1 - \alpha)$, or in other words, an alpha of 0.05 indicates a 95% confidence level.

To get the z value for a 95% confidence interval (remember we need to exclude 2.5% or 0.025 of the area on both sides), we search the z -table for the value $1 - 0.025 = 0.975$. This value corresponds to $z = 1.96$. This z value is then used to calculate $[L(\mu), U(\mu)]$ as follows:

$$L(\mu) = \mu - z \frac{\sigma}{\sqrt{n}} \quad (\text{C.3})$$

and

$$L(\mu) = \mu + z \frac{\sigma}{\sqrt{n}} \quad (\text{C.4})$$

Unless otherwise stated, in this thesis we have considered a CI of 95% in all the simulations. All simulations were run 30 times and the average and standard deviation used with the z value of 1.96 to calculate the CL.