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Electricity Tariff Design and Implementation for the Smart Grid

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Abstract

The electric power system is one of the largest complex adaptive systems, yet its centralized electromechanical operation remains unaltered since its invention in the last century. This model used to be adequate for the previous decades. However, energy demand continuously increases and we will soon be unable to satisfy it with current technology. Additionally, there is a need for reduction in CO_2 emissions. More specifically, in the U.K., the 2008 Climate Change Act mandates an 80% CO_2 emission reduction by 2050. These facts will inevitably lead to the mainstream usage of renewable energy systems during the following years. Moreover, today's power system lacks transparency as customers have no way of monitoring and controlling their energy usage besides reading their monthly bills, communication is one-way, and there is no real supervision of the distribution system. All these factors led researchers to the quest for a new power system model, which was named the Smart Grid. This model is influenced by the World Wide Web, operating in a decentralized manner, with many producers and consumers of various generation capabilities and consumption patterns. Consumers are able to obtain real-time information on their energy and carbon footprints with the use of smart-metering devices but, most important, are capable of responding appropriately to signals they receive from the Grid. Along with the technical issues, a transformation of current business models is essential. Although electricity market deregulation has decreased wholesale prices, this change has not been perceived by final customers. This is due to the fact that most of electricity trading is performed through long-term contracts between generators and suppliers via risk management instruments so that customers can pay fixed prices no matter what is the true cost of delivery on behalf of the utilities. In this project we have made an effort to study customer bill savings for a variety of electricity tariffs on real data from a U.K. neighbourhood. New types of tariffs that have been previously applied to large industrial and commercial clients have been tested on a population of residential customer agents. To our knowledge, this is the first time that an agent-based simulation for this type of tariffs has been performed in the U.K. based on a realistic wholesale market setting. Our results show that both customers and suppliers could benefit from real-time pricing rates in terms of profit attained as well as corresponding risk.

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Contents

List of Figures

Chapter 1

Introduction

Electricity is undoubtedly one of the most valuable modern commodities and probably the most important human invention of the 20^{th} century. People nowadays have a huge variety of appliances that provide comfortability and quality of life, such as electric ovens, televisions and mobile phones that could not otherwise operate without the existence of current power systems. Additionaly, other commodities that are considered de facto and are essential for our survival, such as light and heating, utilize electricity as raw material. However, electricity demand levels continuously increase along with prosperity levels, something which was not expected when the first power systems were implemented, so current electricity infrastructure is strained and a redesign of the whole system seems necessary. Governments and professionals have well understood this problem and are now making strong efforts to achieve this change. This can only be done by upgrading current old systems and enhancing them with new types of sources, such as renewable solar or wind power, as well with novel ways of managing the trading of this unique commodity. So, let's take a closer look to their plans for the electricity future.

1.1 The Smart Grid

It was little more than a century ago when Thomas Alva Edison launched his company to provide electric lighting to the general public, signaling the advent of the electricity industry. However, Edison was one of the most fanatic proponents of direct current (DC) systems which had severe problems with transmission losses. This is the main reason for the prevalence of alternating current (AC) technologies, as was early foreseen by George

Westinghouse, one of Edison's strongest competitors. Nevertheless, it was undoubtedly Samuel Insull who pioneered the business model of electricity markets. Insull soon realized that loads should be expanded and integrated so that generation expenses could be evenly distributed among customers, hence a regulated natural monopoly seemed to serve his ideas in the most efficient manner. Vertical integration was the dominant business model until 1990 when market deregulation made its appearance.

But, unlike most modern industries which started reforming their operation 25 years ago, exploiting the advances in information and communication technologies (ICT), current electric power system has preserved its old electromechanical properties since its invention with the exception of minor additions of monitoring facilities to the transmission lines. This fact is not in accordance with current needs. Electricity demand levels are continually rising and this increase will be even more apparent with the adoption of plug-in hybrid electric vehicles (PHEVs), so new generation factories have to be constructed and operated to cover this increase; it is important to note that, currently, in the U.S., 25% of generation and 10% of distribution facilities are necessary for serving only 400 hours of energy per year [10]. Additionally, electricity and information flow is one-way, so customers have no means of measuring and efficiently altering their consumption habits. Moreover, the availability of fossil fuels is reaching its bottom line so incentives for investing on renewable energy and storage instruments should be provided. However, probably the most important side effect of today's electricity system is the increasing levels of carbon dioxide emissions. Governments have well understood this problem and have agreed on measures to deal with it. More specifically, in the U.K. alone, carbon emissions are required to be reduced by 80% until 2050, while at the same time the European Union mandates the generation of 35% of total demand through renewable resources [11]. To manage this scale of requirements a new revolution in the electricity landscape is necessary. This is the *Smart (Electricity) Grid*, shown in Figure 1.1.

According to Peter Fox-Penner, member of the Brattle Group consulting firm, the Smart Grid is a way of "*combining time-based prices with the technologies that can be set by users to automatically control their use and self-production, lowering their power cost and offering other benefits such as increased reliability to the system as a whole*" [12]. Although there is no unique definition, the Smart Grid vision encompasses the whole system, ranging from the generation through the transmission and distribution networks

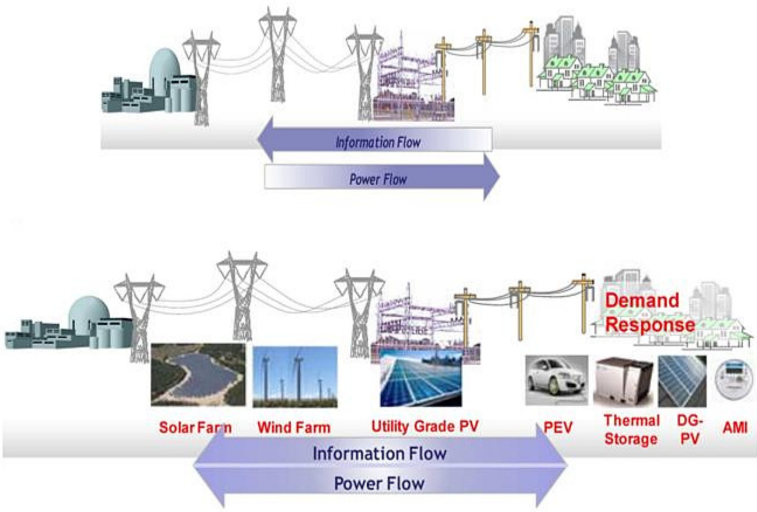

Figure 1.1: Power - information flow under the traditional electricity system and the Smart Grid [1].

to the customer part, and was successfully characterized as the "Internet of Energy" [13].

Clark Gellings, Vice President of Technology at the Electric Power Research Insitute (EPRI), identifies some key properties of the Smart Grid [14]: The Smart Grid should supply electricity reliably, optimally generating and storing it, while at the same time incorporating distributed resources and controllable loads to minimize cost. Production and delivery should be secure and environment friendly and all critical components should be effectively monitored. Currently there is a variety of initiatives with different viewpoints, but a common target, which is paving the way for the implementation of this new, innovative system [14]:

- *IBM's Vision*[1]: IBM emphasizes on the customer participation. They believe that monitoring, smart metering and distributed generation deployment using open standards will greatly influence current industry operation.

[1] `http://www.ibm.com/iibv`

- *IntelliGrid*^{SM}[2]: EPRI's initiative proposes an implementation of a platform where ICT and energy delivery are integrated.
- *GridWise*^{TM}[3]: This is a project of the U.S. Department of Energy (DOE) which focuses on the implementation and deployment of modern distributed generation facilities.
- *U.K. SuperGen Initiative*[4]: Two plans (mid-term and long-term) have been set in the U.K. and are split into seven distinct workpackages, ranging from system security and decentralization to customer participation and micro-grid generation.
- *European Union Smart Grid*[5]: The European Union has initiated a number of projects for the integration of renewable resources into the grid. They insist on creating a common EU liberalized market where all customers can participate as well as setting common standards and regulations.
- *General Electric (GE) Vision*[6]: GE foresees a Grid which is smarter than all its components and provides benefits for both the utility and ICT industry. They also emphasize on distributed generation, smart homes exploiting demand response opportunities, plug-in electric vehicles (PEVs) that store and produce energy, and efficient, secure, qualitative power delivery.

1.2 The Multi-Agent Systems Paradigm

The envisioned Smart Grid is a self organizing complex system (SOCS) [15], as it is an open system which comprises diverse classes of self-interested participants with various types of interactions, while at the same time manages to settle at a macro-level emergent stable state. Hence, an agent-based approach seems appropriate for modeling this electricity system.

There are many definitions for a software agent but the most widespread is that of Michael Wooldridge and Nicholas R. Jennings according to which

[2] `http://www.epri-intelligrid.com`
[3] `http://www.electricdistribution.ctc.com`
[4] `http://www.supergen-networks.org.uk`
[5] `http://www.smartgrids.eu`
[6] `http://www.gepower.com`

an agent is "*a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its delegated objectives*" [16]. For the agent to be intelligent, it should also be able to sense and react to changes in its environment (*reactivity*), to take the initiative so as to achieve its targets (*proactiveness*), but also to be capable of interacting with other entities in its environment (*social ability*) [16]. Following their last property, agents are typically organized in societies, called multi-agent systems (MAS) where they can cooperate or compete for resources through a negotiation process.

Software agents can be useful to this new electricity system in a variety of ways, but we can categorize them in two major areas. First of all, they can be used for validation of any novel rule concerning structural reforms or business models by simulating broad parts of the new, yet unseen, Smart Grid; the recent Western U.S. energy crisis of 2000-2001 due to the gaming of the new deregulated market from Enron led to an estimated cost of $33 billion for the citizens of California, uncovering the need for cautious market design in novel domains [12]. What's more, agent technology is now mature enough to be incorporated in real systems. One of the key attributes of the Smart Grid is real-time flow of information among its stakeholders (customers, utilities, regulators, operators), hence it is almost impossible to analyze this huge amount of data. Intelligent agents therefore can exploit the computational abilities of modern computers to perform human tasks so as to optimally serve their owner's objectives and at the same time guarantee the system's security.

1.3 Problem Definition

As we have already mentioned, current electricity system provides the customers with no means of measuring and controlling their loads and one of the main targets of all Smart Grid initiatives is their equipment with advanced metering infrastructure (AMI) to aleviate this problem. Additionally, more and more customers will begin to supply their homes with distributed energy resources (DER) such as micro-storage devices, micro-combined heat and power (μCHP) systems, and small-scale renewable source generation systems. PEVs will also gradually replace conventional vehicles with the help of initiatives such as this of U.S. president Barack Obama, who set a target of one million electric cars in his country by 2015.

In this complex personal grid of heterogeneous, intermittent generation systems and consumption devices, a customer must learn how to optimally utilize relevant technology to dynamically react to price signals sent by his contracted retail service, known as demand response (DR), and exploit his generation / storage capacity such that he maximizes his expected utility. However, this is not the case for a typical person, who has neither the time nor the expertise to handle this type of information. Additionally, electricity market deregulation increases competition for suppliers who will soon be able to provide dynamic pricing contracts to their customers based on their consumption profiles and running wholesale market prices, benefits currently enjoyed only by large industrial businesses. However, large-scale experiments with real customers are difficult to conduct, as careful considerations have to be made so that both customer participation is guaranteed for the results to be valid but also great amounts of money are needed to provide customers proper incentives in a realistic scenario. Thus, a simulation seems to fit well in this setting.

1.4 Dissertation Contribution

In this work, we have used real consumption data from a U.K. neighborhood to assess the benefits of real-time pricing. More specifically, we have implemented various types of electricity tariffs under a realistic market scenario to compare customer monetary benefits from switching to dynamic, real-time pricing which is one of the most crucial parts of the new Smart Grid paradigm. This is the first time to our knowledge that a novel, two-part RTP tariff designed for industrial customers is tested on residential U.K. data.

Our results show that real-time pricing can benefit both customers and suppliers with different risk aversion levels as long as the tariff is properly designed and implemented. Classical financial theory and risk management were used and potentials for future widespread adoption seem to be favorable.

1.5 Dissertation Structure

The rest of this report is organized as follows:

In Chapter 2, we provide a short introduction to the current business model of electricity markets. More specifically, we shortly describe the operation of current U.K. electricity market as well as some common risk management instruments that constitute a crucial part of its trading.

Chapter 3 provides a summary of previous agent-based models used in the modelling, simulation and optimization of power systems and electricity markets.

Then, in Chapter 4 we introduce the concept of demand response along with its benefits for all entities in the electricity landscape and issues arising from its widespread application.

Chapter 5 deals with the challenge of designing electricity tariffs, listing the advantages and disadvantages of commonly used as well as innovative rates.

In Chapter 6, we present our analysis and simulation results for a population of customers under different tariff charges as well as an attempt to create portfolios of these tariffs.

Finally, Chapter 7 concludes this report and proposes directions for future work.

Chapter 2

Electricity Markets

In this chapter, we first make an introduction to the separate but equally valuable parts of electricity markets after deregulation. We then discuss about the details of the U.K. corresponding market and finally present some basic economic notions from the field of risk management, as it has been applied in the electricity sector.

2.1 Market Operation

During the 20^{th} century, the prevalent type of electricity business model was that of the *vertically integrated monopolies*, where electricity providers have unique access and control of the four main parts of the system [17]:

- *Generation*: comprises generating companies (*gencos*) that own power plants of various technologies and sell the energy that has been produced as well as other services, such as voltage control and spinning reserves (i.e. expensive but quickly available types of power generating plants used to balance real time supply and demand).
- *Transmission*: is the high voltage electricity network through which energy is transmitted over large distances so that losses are minimized. Companies owning relevant equipment are called transmission companies (*transcos*) and their operation is controlled by the Independent System Operator (ISO), which is responsible for the robust and safe function of the whole system.

- *Distribution*: is the low voltage (typically 220 Volts) electricity network for the transmission of energy over medium and small distances, such as cities or small regions. The entities comprising this network are called distribution companies (*discos*) and operate under the supervision of the ISO.

- *Supply* or *retailing*: consists of all retail companies (also called suppliers) that resell energy to the final customers (residential, commercial, industrial), acting as intermediaries between them and the producers.

According to the vertical unbundling model (Figure 2.1), a publicly owned utility was able to optimize both the operation and coordination of the aforementioned substituent components but also to guarantee cheap, secure and unfailing electricity supply for everyone, no matter what was the cost of installation and maintenance of the essential equipment for the utility. Hence, given a fixed, regulated profit percentage, utilities should only make an effort to minimize their short-term cost of operation and carefully define their long-term investment strategies. The latter was the main flaw of this model, as there was no real incentive or punishment of the involving parties for any harmful decision, leading to significant inefficiencies and customer bill increases [18].

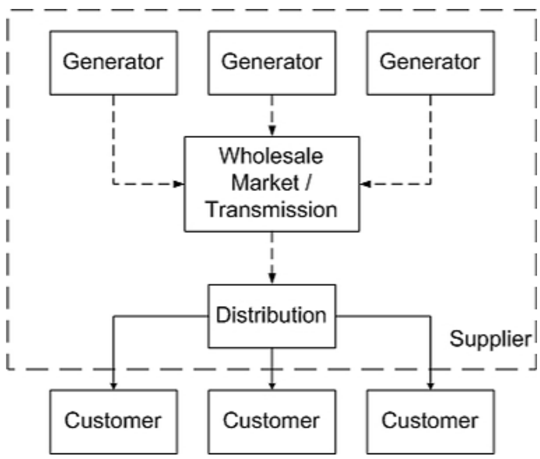

Figure 2.1: Vertically integrated monopoly.

This fact was early seen by economists who believed that competition could increase efficiency and lower costs for the customers. Under this deregulated environment, which is continually expanding worldwide, generation and retail services are traded in their own free exchanges, whereas transmission and distribution networks operate under the supervision of a publicly owned ISO (Figure 2.2). However, some economists insist that the latter should also be deregulated using similar arguments as before [19].

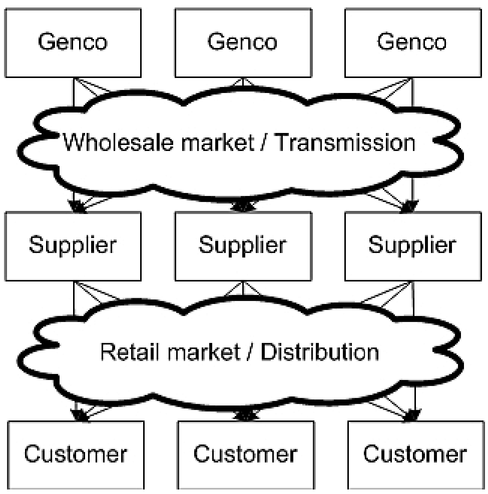

Figure 2.2: Fully competitive electricity market.

2.2 The U.K. Market

After the end of the second world war, U.K. had nearly 560 utilities [20]. The grid was further separated in 14 areas with different ISOs. On 1990 the privatisation of the electricity market followed and an innovative for its time day-ahead electricity pool market for wholesale trading was established. Deregulation in England and Wales started at the same time, after the liberalisation of the gas market, and continued in stages from 1998 until 2002. Transmission and distribution (T&D) networks were gradually sold from monopolies to new players which were able to access all T&D information in a transparent and fair way [21]. Current electricity market took its final form in 2000 with the introduction of the *new electricity trading arrangements* (NETA) to replace the old daily pool market [22]. A final transformation to include Scottish operators was implemented in 2005 (known as BETTA) [23]. According to this new mechanism, there are two organized markets, the *UK pool exchange* (UKPX) and the *balancing market*. However, the majority of trading (almost 95% [24]) is performed via bilateral long-term agreements, called the *over-the-counter* (OTC) market. UKPX is a day-ahead uniform price market, providing half-hourly spot prices (equal to the system marginal price), based on participants' initial physical notifications one day before actual consumption, and closes one hour before real-time energy dispatch, called the "gate closure", when participants report their final physical positions (i.e. predicted aggregate load and generation bids). After that, a discriminatory pricing *balancing market* is operated by the ISO which receives bids for real-time power supply (from expensive but flexible generators offering ancillary services) and demand (from utilities with underestimated consumption predictions) increments/decrements (called *top-ups* and *spillages* respectively) such that any time demand is equal to supply. Top-ups are charged at the system buy price (SBP) whereas spillages are priced at the corresponding sell price (SSP). SBP and SSP are generally unprofitable for the trading counterparts to deter arbitrage opportunities. Only a small percentage of electricity, nearly 3%, is traded in this market and participation is voluntary. Currently, there are 12 active electricity and gas utilities in England and Wales [20].

2.3 Risk Management

Energy trading is a new, complex and volatile market as electricity is a flow commodity, which means that demand must always equal supply in real time, and extremely expensive to store in large amounts. Another reason is that the quality of transmitted power (i.e. A.C. frequency) must remain in acceptable levels to achieve reliable and safe operation. Moreover, electricity value is highly driven by weather conditions and market operations for the relevant raw materials used to produce it [25].

Given this complexity, a market participant faces high levels of uncertainty in both prices (*price risk*) and quantities (*volumetric risk*) traded. The former is linked to the volatility in spot prices due to uncertainty because of its competitor and counterpart strategies, whereas the latter refers to the uncertainty due to customer power consumption variation. Hence, risk management strategies which transfer the risk to other parties and protect against large losses are commonly used in energy markets.

The vast majority of electricity trading between suppliers and generators is conducted via bilateral *forward* contracts. A forward is a contract for the obligation of delivery on a specific future date of a prespecified quantity of power at a predetermined price (called the strike price). In this way both suppliers and generators hedge their risk against spot price volatility. The payoff of such a contract is equal to the difference between spot prices at delivery date and agreed price [26]. A similar instrument is the *future* contract, which has the same structure as a forward but is only traded in organized exchanges and it usually encompasses small quantity values.

A typical forward contract duration can range from few days to some years ahead. As energy has to be continuously delivered, both trading counterparts have to construct short-term and long-term forward curves which can be viewed as portfolios of daily forward contracts for a specified period, creating positive or negative cash flows as Figure 2.3 illustrates. In this case, the buyer of the forward receives an amount which is equal to the difference of the average spot price for the period agreed from the corresponding strike price.

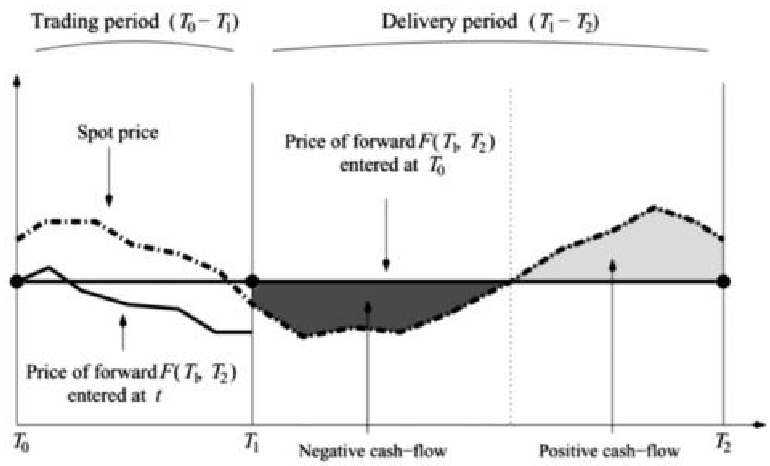

Figure 2.3: Constructed forward curve [2].

Another well known derivative is the *option*. This is a contract giving its shareholder the right but not the obligation to buy (call option) or sell (put option) a predetermined amount of electricity for a price. If the strike price is lower (higher) than the spot price at expiration, then the owner of a call (put) option can buy (sell) the underlying commodity and sell it back (buy it) at the wholesale market, making profit because of price differences.

There is a great variety of other electricity derivatives for trading generated and transmitted electricity, borrowed from traditional markets ([26] contains a summary of these). In all cases, an accurate model of the underlying wholesale price movement is the most important ingredient of successful management, which is far different than classical economic models, as electricity exhibits strong mean reversion and does not follow a Geometric Brownian motion [25]. Additionally, local service utilities must also hedge their volumetric risk, which is usually done via weather derivatives.

Chapter 3

Software Agents for Electricity

In this chapter, we describe available agent-based tools for the simulation of the power system and electricity markets along with their pros and cons. We then present some state-of-the-art studies that are focused on the Smart Grid.

3.1 Available Tools

Electrical engineers, economists as well as computer scientists have long used agent-based systems to model the broad electricity marketplace, ranging from the customer to the producer level.

The Simulator for Electric Power Industry Agents (SEPIA) [27] is one of the first general purpose systems for modeling electricity markets. Simple Reinforcement Learning techniques, such as the famous Q-learning [28] and a modified version of the Roth Erev algorithm [29], are used to guide the behavior of generators and suppliers. The latter are situated in virtual zones (regions). However, there is no entity undertaking the role of the ISO. On the other hand, the Electricity Market Complex Adaptive Systems (EMCAS) platform incorporates both an ISO and a regulator [30]. In EMCAS, there are three business layers (bilateral contract, pool and transmission/distribution market) along with the physical and regulatory ones. Moreover, there are six distinct planning periods for the markets, ranging from the short-term real-time to a year-ahead planning horizon for the generators, and their learning can be categorized as either *observation-based* or *exploration-based*. MAIS is an agent-based system that simulates U.S. wholesale prices and has been tested on real data during the period of the California energy crisis [31]. A recent general-purpose platform is Sun and Tesfatsion's Agent-based Modeling of Electricity System (AMES) framework, built on Repast [1], which is a Java-based open-source platform, thus making it easily extensible [32]. Repast was also the basis for the PowerACE system, which can be used to design and evaluate new markets for the exchange of carbon-dioxide emissions [33]. A detailed review of the aforementioned systems can be found in [34] and [35].

Bunn and Oliveira [22] made an effort to study the effects of the new electricity trading arrangements (NETA) that have been recently applied in the U.K. electricity market. More specifically, they have modeled the operation of the new pool and balancing markets on a single-day basis and have shown that suppliers face a higher risk than producers in these new markets. Additionally, producers' collusion possibilities increase with the corresponding capacity margin when regulation is not enforced. Finally, their results show that over-hedging can be unprofitable for the suppliers and vice versa. Similar studies for the Belgian [36] and the German [37] markets provide insights on how both producers and the ISO could optimize their operations with the use of linear programming techniques.

3.2 Novel Approaches for the Smart Grid

The advent of the Smart Grid has revived the interest of AI practitioners, as the need for automation of both home and market procedures creates space for innovation. Vytelingum et al. [38] have recently presented a novel mechanism to deal with the automated trading of electricity which is based on the Continuous Double Auction (CDA). In their work, they incorporate a fair congestion management framework for the transmission lines, so that higher priced transactions are favored against lower ones, and there is a balancing mechanism for real-time management of demand and supply. The authors validate their results using simple traditional as well as state-of-the art CDA trading strategies, namely the Zero-Intelligence [39] and Adaptive Aggressiveness [40] strategy respectively, which are able to achieve values of efficiency in the range of 86% - 99%. The same authors consider an agent-based microstorage model to optimize (i.e. minimize cost) customers' individual and aggregate loads [41]. They perform a game theoretic analysis and empirically find that 38% of the U.K. population will adopt storage at Nash

[1] `http://repast.sourceforge.net`

equilibrium where an average saving of 8.54% is achieved in customer bills. In a more recent work, they consider the same type of customers [42] study another important field, the Vehicle-to-Grid (V2G) power system, according to which PEVs offer their batteries for load balancing (ancillary services) when idle (90% of the time on average). More specifically, they consider the problem of PEVs coalition formation using simple adaptive strategies. V2G is also the topic of Vandael et al. [43], who compare an optimal quadratic programming solution with a MAS on how they manage to flatten PHEV load, thus inducing DSM. They conclude that the computationally tractable solution using a MAS leads to a peak reduction of 5%. Vytelingum et al. [44] present an environmentally friendly solution to the problem of optimizing storage for the consumers of a green energy utility through appropriate control signals. This homeostatic-based control system achieves a reduction up to 21% of green wastage for the utility and a corresponding decrease up to 10% for the customer bills compared with a traditional real-time pricing tariff. Given the necessity of designing proper market rules for the electricity industry, the Trading Agent Community [2], which has been organizing agent competitions (known as TAC) since 2002, has announced the beginning of a new game, called TAC Energy [3], for 2011. This game, which follows similar concepts to the work of this dissertation, each entrant represents an energy broker which offers appropriately designed tariffs to its customers based on bilateral agreements with the producers. The latter can be conventional power plants as well as factories exploiting intermittent, renewable types of electricity, such as solar and wind power. The customers themselves could own small CHP facilities that are able to feed back energy into the grid for some monetary value. Finally, TAC Energy encompasses PEV consumers, which agree on special tariffs for both energy consumption and feed-in. It is important to note that it is the first time that real data, taken from the cities of Gopingen and Freiamt as part of the MeRegio project [45], for both prices and consumer preference modeling are used in this competition.

[2] http://tradingagents.org
[3] http://www.tacenergy.org/

Chapter 4

Demand Response

In this chapter we introduce one of the most important parts for the success of the Smart Grid, namely demand response. We first present a definition of this notion and then describe some common demand response practices. Finally, we discuss about its importance giving concrete examples of its success as well as relevant concerns.

4.1 Definition

One of the main problems of current electricity markets is the lack of customer price elasticity of demand (i.e. percentage change in quantity in response to a one percent change in price), as customers are only able to communicate with their suppliers, paying at a fixed price no matter what is the underlying cost for the utility and hence are isolated from the wholesale market, although there is an abundance of evidence suggesting that they would otherwise respond to its dynamics [46]. This fact along with customers' habits and low cost of electricity compared to output products for the industrial sector provides generators opportunities for market power exercise and induces high price spikes [47]. Demand response is an effort to alleviate this problem.

According to the Federal Energy Regulatory Commission, as *demand response* (DR), also known as *price-responsive demand* (PRD), can be characterized any "*action taken to reduce electricity demand in response to price, monetary incentives, or utility directives so as to maintain reliable electric service or avoid high electricity prices*" [3]. In other words, DR is any price-based effort to increase customers' price elasticity of demand, as Figure 4.1

illustrates. Sometimes direct load control (DLC) through appropriate signals is also incorporated in this definition, although the term *demand side management* (DSM) was later adopted instead. DR not only reduces the risk of black-outs but also leads to investment savings in generation (consequently reducing carbon dioxide emissions) and increases market efficiency by letting customers manage their consumption based on the actual cost of production.

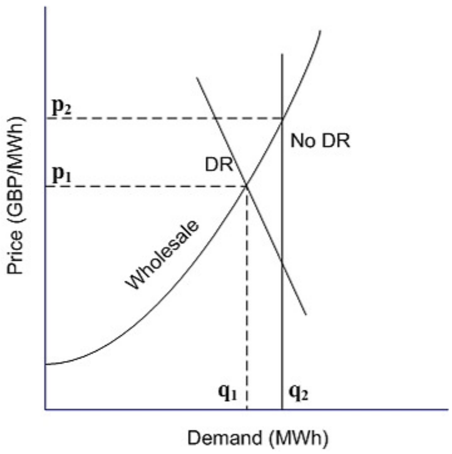

Figure 4.1: Effect of DR on electricity prices.

4.2 Categorization

DR schemes can be categorized in two broad classes, namely *incentive-based* DR and *time-based* rates [48, 14]. The former comprises curtailment rates (i.e. bill reduction for load reduction), ancillary services (i.e. bids for load reduction in the ISO market), capacity markets (i.e. predetermined load curtailments when capacity problems arise) as well as bidding programs (where customers submit bids for load reduction based on their preferences), whilst the latter refers to specific types of tariffs that indirectly incentivise price-responsive customers to change their consumption patterns, such as time-of-use (TOU) rates, real-time prices (RTP) and critical-peak pricing tariffs (CPP) [3]. Customers perceive DR as either load reduction or load deferral with varying degrees of comfort loss, although onsite generation can minimize their impact. The amount of demand reduced is equivalent to the offering of an equal (virtual) amount of generated load, so the term *negawatt* was coined to characterize a watt of DR reduction.

Independent System Operators (ISOs) and utilities worldwide accommodate various types of DR programs. In the U.S., we can distinguish the following categories:[1, 49]:

- *Emergency DR* or *installed capacity special case resources* in extreme situtations when demand curtailment is essential.
- *Real-time DR* during high pricing periods where customers are charged at real-time or hourly tariffs. To reduce associated risks, in some cases, customers are allowed to pay a prespecified amount of money for a percentage of their demand through forward energy contracts connected to the wholesale market.
- *Day-ahead DR*, which comprises contracts with customers for reduction based on the corresponding day-ahead market prices so that they are able to more effectively plan and optimize their consumption pattern for the next day
- *Demand-side ancillary service program*, where load savings are used as spinning reserves and customers are usually rewarded with real-time prices.

There are two major types of evaluation for DR impact, a *retrospective* and a *prospective* [50]. The former is an ex-post evaluation where the amount of load and expenses saved is calculated after the implementation of the DR program, whereas the latter refers to the estimation of the program's impact for future years (ex-ante). Common techniques to measure real impact is to incorporate DR-free control groups, complex regression models to measure both consumers' baseline loads and variability, so that only desirable stable customers participate in the program [50].

4.3 Historical Facts

DR is not a new concept. First, William Vickrey in 1971 [51] and then Fred Schweppe and his colleagues in the 1980s have expressed their ideas for a price-responsive efficient and reliable Grid [52, 53, 54, 55]. However, large industrial and commercial customers are the only participants enjoying its benefits. In the U.S., only 5% of customers implement some form of DR (see Figure 4.2), mostly through interruptible and TOU tariffs, although there is a potential for a 37,500MW load decrease [3]. This fact can be linked to the absence of AMI for the majority of customers due to their high cost of purchase and installation as Figure 4.3 illustrates. It is important to note that according to FERC, only 259 among 2,620 utilities in the U.S. have implemented some form of price-based DR [3], starting from simple performance-based contracts (i.e. contracts for efficiency upgrades) and then utilizing risk management instruments [56]. In the U.K., there are currently only two major, simple residential DR programs in the U.K., namely Economy 7 and 10. The former provides seven hours of low prices during the night and the latter offers ten hours of corresponding prices distributed during a day [57]. However, in 2006 only 16% of U.K. citizens were subscribed to Economy 7 program [58]. The Smart Grid will provide residential customers, which account for 29% of total electricity in the U.K., advanced DR programs, which will hopefully lead to overall electricity price reduction and investment savings.

The first DR program focused on the Smart Grid was Pacific Northwest National Laboratory's (PNNL's) Olympic Peninsula Project in Sequim, Washington, U.S. [59]. The target of the project was to demonstrate reliable and robust operation of an isolated grid, called a *microgrid*, with the utilization of intelligent appliances and control systems via a market-based approach. More specifically, there is a shadow market where both consumers and suppliers submit bids for electricity at 5-minute intervals. One hundrend and twelve consumers were equipped with Whirlpool's appliances that could send and receive control and pricing signals to reduce their load. Each household was given an initial amount of money for the experiment to be realistic and was then required to select a type of contract (TOU, CPP or RTP tariffs). Although this is one of the most valuable projects, proving the attainability of this new Grid, the implementation of similar experimental programs is difficult because of their prohibitive cost; for the Peninsula Project, household equipment cost was approximately $1000 per customer [12]).

4.4 Advantages and Disadvantages

According to S. Braithwait[49], average peak demand reduction for residential customers varies from 10% to 50%, depending on the type of DR program followed (tariffs used and incorporation of enabling technologies, i.e. devices that facilitate control of appliances), but generally consumers with high cooling or heating demand are the most responsive customers. It

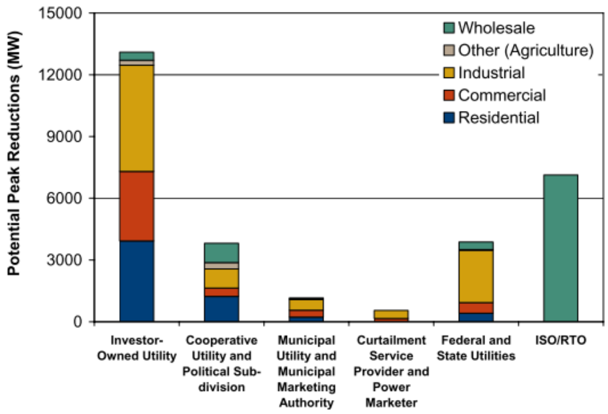

Figure 4.2: Demand response contributions by entity type and customer class [3].

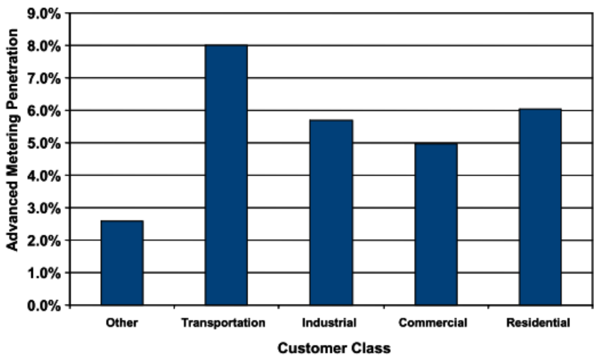

Figure 4.3: Advanced metering infrastructure penetration by customer class [3].

is hence important to know the demand profile of a consumer as well as his corresponding electric devices to be able to model and predict his behavior. Thus, DR should be a three stages effort, starting from an individual appliance through an in-home synchronization to a multi-consumer indirect coordination [10].

DR benefits include among others short-term market savings [47, 60, 48], reducing price peaks and corresponding volatility, long-term savings from deferral of unnecessary investments on power plants [61], reliability and power quality guarantee [62], avoiding black-out effects (scientists from the EPRI found out that the lack of DR was one of the main reasons that led to the California's energy crisis [63]) as well as environmental benefits [3].

On the other hand, there are some costs associated with DR implementation [48]. Besides relevant discomfort issues, customers have to install and operate costly enabling technologies so that they can monitor and control their appliances. Moreover, onsite generation imposes expensive investment and running costs, such as fuel and maintenance expenses. Finally, customer education is one of the most important issues for a utility, so personnel and resources must be engaged.

Results for the customer response to DR are ambiguous. The vast majority of studies focuses on customer price elasticity of demand. However, their results diverge as customers have different incentives for load reduction based on the type of project involved. When bill reductions or lack of expenses are guaranteed, participants have no real incentives to realistically alter their consumption pattern.

Chapter 5

Tariff Design

In this chapter we delve into the details of the electricity tariffs that are currently being implemented in residential and industrial settings. We present the advantages and disadvantages of each tariff and introduce the novel, two-part real-time tariff along with its variations.

5.1 Electricity Tariffs

One of the benefits of DR is the potential for incorporating risk management strategies for both suppliers and final customers, thus hedging their corresponding price risk. In this chapter, a variety of tariffs and relevant hedging instruments are presented.

5.1.1 Flat rate

The simplest type of tariff is the traditional *flat tariff*, according to which each customer pays a fixed price per KWh no matter how much it costs the utility to deliver it, thus isolating retail from wholesale markets and creating no real incentives for efficient price response. We can identify two main cost components, namely the average delivery cost and the risk premium for hedging spikes in the wholesale price [64, 65]. This tariff has been the prevalent type of pricing during the previous decades and inevitably increases electricity bills as utilities have to hedge their risk on the long-term. A slightly advanced version of this tariff utilizes different price levels based on the season that it is applied. As Ahmad Faruqui, member of the Brattle group energy consulting firm, argues [9], a fixed price tariff is unfair as it incurs high levels of risk premiums and favors customers having positively correlated loads with spot prices against negatively correlated ones. Moreover, it gives generators the opportunity to exercise market power.

5.1.2 Increasing-block Tariff

A variation of the flat rate is the *increasing-block tariff* [4], a ladder-like pricing mechanism where customers pay a low, fixed price until a consumption threshold is reached after which they pay higher amount. There could also be more than one thresholds (tiers) included in this tariff. An example of such a four-tier rate charged by Southern Electricity Edison utility is illustrated in Figure 5.1.

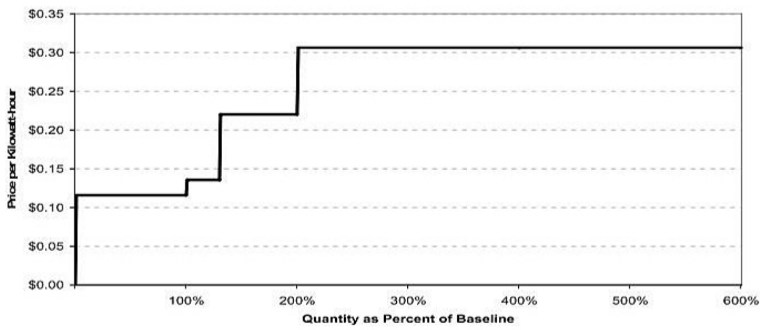

Figure 5.1: Increasing-block tariff of Southern Electricity Edison utility [4].

5.1.3 Time-Of-Use Tariff

The first type of DR tariff is the *time-of-use* (TOU) rate (Figure 5.2), where each customer pays a higher amount of money (on-peak prices) for the peak hours during the day and lower (off-peak) prices during the night, so that they are incentivised to shift their load during low wholesale cost, daily periods. The risk premium in this case should be lower than the flat-rate one, as the supplier shares a portion of his risk with the customers. This type of rate is more appropriate for customers who can defer or regularly consume their loads during the night [47]. However, even in this case, prices remain fixed for a long time and do not adequately represent wholesale market volatility. TOU programs started in the U.S. in 1975 with 16 different programs sponsored by the Federal Energy Administration until 1981 [46, 3] in five different states. Since then, the vast majority of utilities have incorporated this tariff in their programs. However, the difference of on-peak and off-peak rates should be carefully designed, otherwise trivial or unprofitable bill reductions can be observed, as was the case with the Puget Sound Energy's program in 2001 [3]. Another variation of TOU prices is the *variable peak rate* [66] where off-peak price remains fixed but on-peak rate is determined on a daily basis so as to reflect spot prices.

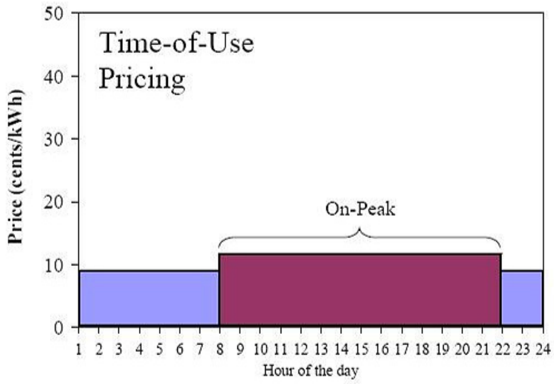

Figure 5.2: Time-of-use tariff.

5.1.4 Critical Peak Pricing

Highly peaked prices are usually observed for a small number of days during a year, directly connected with extreme low or high temperatures. Hence, another proposed tariff, called Critical Peak Pricing (CPP) (Figure 5.3), charges customers extremely high prices (more than their real wholesale counterpart) under predetermined trigger conditions for these days. This type of rate is thus an additive one and can be combined with any other (usually TOU) tariff. Several variations of this tariff have been introduced [3]: Fixed-price CPP (CPP-F) where there is a standard amount of time and duration of critical events but no information about the days to be enforced is provided. On the other hand, variable-period CPP (CPP-V) does not incorporate any predefined time, duration or day of price peaks. The variable peak pricing (VPP) rate includes standard on- and off-peak prices but peak prices are calculated based on the daily wholesale prices so as to link the corresponding market with the retail one. VPP is thus a voluntary pricing program. Finally, Critical Peak Rebate (CPR) is similar to CPP but instead of paying extra charges during peak hours, customers are incentivised to reduce their load by receiving a rebate for every KWh they save compared to their historical CBL [67]. In the U.S., there are currently 25 utilities offering CPP tariffs [3].

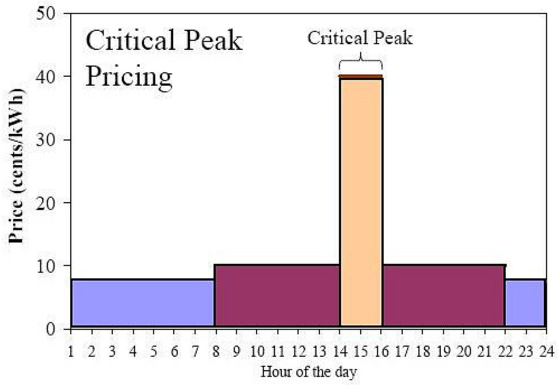

Figure 5.3: Critical peak pricing tariff.

5.1.5 Real-Time Pricing Tariffs

Traditional Real-Time Pricing

Finally, the ultimate form of wholesale-retail market connection is the *real-time pricing (RTP) tariff*, according to which load consumption is charged on an hourly or half-hourly basis, thus directly exposing wholesale prices to the customers. RTP programs can incorporate day-ahead or day-of real-time prices and can be mandatory or voluntary with varying social welfare expectations [68, 3]. In the day-ahead RTP tariff, customers are informed 24 hours in advance about the estimated prices so they are able to plan their next day electricity usage or, sometimes hedge these prices with other financial instruments. In this case, the supplier transfers the larger portion of its risk to the customers, so only a small risk premium is charged. This premium reflects two major types of risks, the volumetric and the price risk. The former refers to the utility's uncertainty for the actual aggregate load deviation from the predicted one, as this deviation will have to be exchanged in the expensive balancing market, whereas the latter refers to the uncertainty on the spot prices due to competition. RTP programs especially benefit flatter-load customers who are inevitably buying smaller electricity amounts at cheaper prices, in contrast to peaky customers who would inevitably pay more, although the corresponding risk premium is much lower [69]. It is important to note that, although RTP programs have been in place since mid-1980s for large industrial customers, it was only in 2003 when Commonwealth Edison utility with the help of Center for Neighborhood Technology (CNT) designed and started the first residential RTP program in the U.S., called the Energy-Smart Pricing Plan [70]. Holland and Mansur [71] have investigated the short-run benefits of RTP using a simulation of the PJM electricity market, and have shown that it can induce both consumer gains (2.5% of the monthly bill) and production cost decrease (59% for oil-fired generation), although average hourly load would increase along with the corresponding NO_x and SO_2 emissions (but CO_2 emissions decrease). Although RTP programs have a great potential for bill savings, it is amazing that only few of them have managed to attract and maintain customer participation. A recent study among 48 utilities in the U.S. shows that, although reductions of 12-33% were achieved, one third of the programs had no participants at all (see Figure 5.5 while 28% of the programs were about to be terminated [5]. Some of the reasons for that include poor marketing and customer support as well as program eligibility limitations that led to the attraction of the largest industrial customers. Severin Borenstein has conveyed a number of experiments to quantify the risk associated with RTP [72]. Bill volatilities are to be expected even in flat tariff settings due to the changing consumption habits, but it is true that RTP prices increase these values due to their stochastic nature (two to four times according to Borenstein). However, his results show that hedging can cover more than 80% of price volatility in customers' bills. The amount of hedging is directly proportional to the customer's load correlation with spot prices. More specifically, Borenstein has utilized data from real industrial and commercial customers as well as spot prices from

California power exchange during the period 2000-2003. He has then created artificial, revenue equivalent flat and TOU rates along with fixed, forward prices (using the actual average spot price for the observed period) and sets hedging volume equal to the customers' CBLs. According to his findings over-hedging can further decrease price volatility.

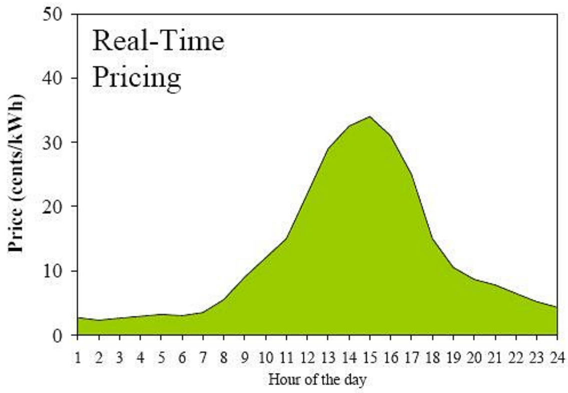

Figure 5.4: Real time pricing tariff.

Two-Part Real-Time Pricing

The main problem with RTP is that clients are usually risk-averse and do not wish to see large deviations in their monthly bills. Additionally, free riders can exploit RTP benefits and obtain profit without altering their consumption habits [73]. Hence, an innovative RTP tariff that has been utilized in the industry is the *two-part RTP tariff* (Figure 5.6) also known as *Block-and-Index Pricing*, which was first introduced under revenue neutrality by Niagara Mohawk Power Co. in 1988, with a program called Hourly Integrated Pricing Pilot (HIPP) [74, 5, 75, 3] for industrial clients under the SC-3A option. According to this tariff, customers pay their previous standard (usually TOU) rate for a fixed baseline load (which is usually their average historical demand before entering the program) and then, each hour per day, they are charged proportionally to their deviation from this baseline load at a price close to but higher than both the market and real-time tariffs. Hence, customers are able to hedge their risk for the majority of their load and then efficiently trade their deviations, inducing DR. In this case

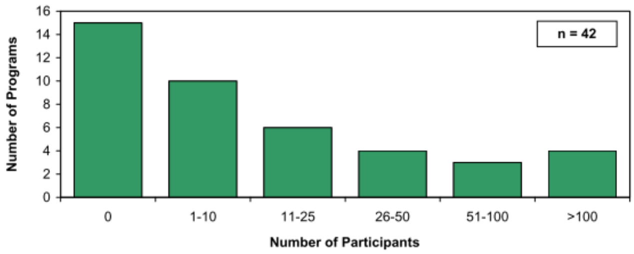

Figure 5.5: Number of participants per RTP program [5].

it is extremely important to select the best suited historical baseline profile in a transparent way so that customers are not able to game utilities. In its first implementation, this tariff included two types of costs, namely the marginal cost of energy and the marginal outage cost (equal to the product of the value of lost load and the loss of load probability), and was combined with a fixed, pre-determined CBL, however a variety of issues arises when customers intentionally alter their load pattern before entering the program. This is why, nowadays, a historical average of the previous ten non-event days is used most of the time and appropriate adjustments are made to the calculated baseline load so as to align it with the most recent consumption pattern. However, more sophisticated techniques are needed for high variability customers [5, 50]. Suppliers are the intermediates between generators and customers, so retail risk management is also an essential part of their business. Common retail hedge contracts include *price caps*, that set a maximum price threshold to protect customers from extremely high spot prices, as well as *price collars* that include both a minimum and maximum price to protect themselves from low wholesale prices. Additionally, customers can pay indexed prices on other fuel or production output as well as contracts for differences that give customers the possibility of exchanging real-time prices for fixed ones. Ins some cases, customers are offered contracts for buying and selling CBL amounts. Nevertheless, these hedges, called *price protection products* (PPPs) are currently limited to industrial clients [76, 69, 5]. In other cases, customers are able to select the percentage of their CBL used for hedging. The latter type of pricing is called *unbundled RTP with self-selected CBL* or *build-your-own (BYO) two-part tariff* [69, 77, 66] and is equivalent to a standard forward contract. A summary of common hedging instruments used along with their corresponding risk levels are illustrated in Figure 5.7. At this point we should note that Georgia Power which has been using this tariff for its industrial customers was the only utility to achieve significant customer participation in its program [78].

Time varying tariffs can be categorized based on two attributes, *granularity* and *timeliness* [77]. The former refers to the rate of intra-day or intra-week price change whereas the second is linked to the time between price announcement and implementation. Hence, flat and minute-to-minute RTP rates can be seen as the two extreme points in the continuum of possible tariffs. Both attributes contribute to the accuracy of the price signal to be sent. Ideally, a tariff should provide reasonable time for customers to respond to the signals and should be accurate enough to reflect marginal

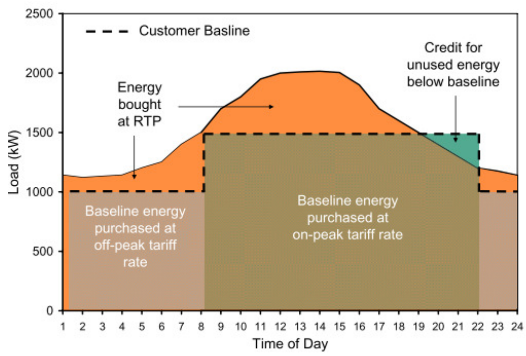

Figure 5.6: Two-part real-time pricing tariff [6].

costs of production and delivery.

5.1.6 Distributed Generation Tariffs

Finally, we should mention two types of tariffs for DG customers, namely *sell-back* and *standby* rates [66]. The former refers to the price that a customer with onsite generation ability should receive to inject power back to the grid whereas the latter deals with the problem of proper charging DG clients for the absence of generation due to maintenance reasons.

Risk	Product Class	Product	Baseline or Part of Baseline	Incremental Usage
HIGH	*Index Type Products*	One-part RTP	N/A	Day-ahead prices
		Purchasing through ISO	N/A	Real-time prices
	Cap Type Products (for price risk)	Cap	Day-ahead prices (risk limited)	Day-ahead prices
		Collar	Day-ahead prices (risk limited)	Day-ahead prices
		DR Technology	Day-ahead prices (risk limited)	Day-ahead prices
	Swap Type Products (for price risk)	Two-part RTP	Hedged	Day-ahead prices
		Swap	Mostly hedged	Day-ahead prices
		Long term supply contract	Hedged	Real-time prices
		Energy efficiency investments	Hedged	Day-ahead prices
		Take-or-pay contract for part of usage	Hedged	Day-ahead prices
	Hedges Covering Price and Volume Risk	Fixed rate contract	Hedged	Hedged
		Time-of-use type tariff	Hedged	Hedged
		Volumetric collar	Hedged	Hedged
LOW		Take-or-pay contract for full usage	Hedged	Hedged

Figure 5.7: Hedging instruments and corresponding risk levels [7].

Chapter 6

Experiments

In this chapter we investigate the effects of different tariffs in a realistic setting. More specifically, we provide an abstract but realistic model of the wholesale market and observe the results of rate enforcement on a population of consumer agents.

6.1 Experimental Setting

For our experiments we have used real electricity load data from a neibourhood provided by a privately owned utility located in Hampshire as part of the Intelligent Decentralised Energy-Aware (iDEaS) project[1]. These data correspond to the half-hourly consumption (48 data points per day) of 7752 customers for the period January - March 2010. However, due to inconsistency issues, we had to remove corrupted data and kept corresponding loads for 5933 agents. Whenever data was missing, we have replaced them with the customer's average load for the same month. Figure 6.1 illustrates the average aggregate demand and corresponding volatility. The results for weekdays and weekends are plotted separately, as consumers behave similarly during working days but have different habits on their weekends. We can see that there is an apparent peak during the afternoon when most of people return to their homes and turn on their appliances. The estimated distribution of the loads and their volatility (i.e. standard deviation) for all available data is shown in Figure 6.2. The estimation of the probability density function (PDF) is based on the Parzen window method [79]. The PDF

[1] `http://www.ideasproject.info/`

seems to be leptokurtic with a positive skewness due to the extremely high load and volatility of a small customer percentage.

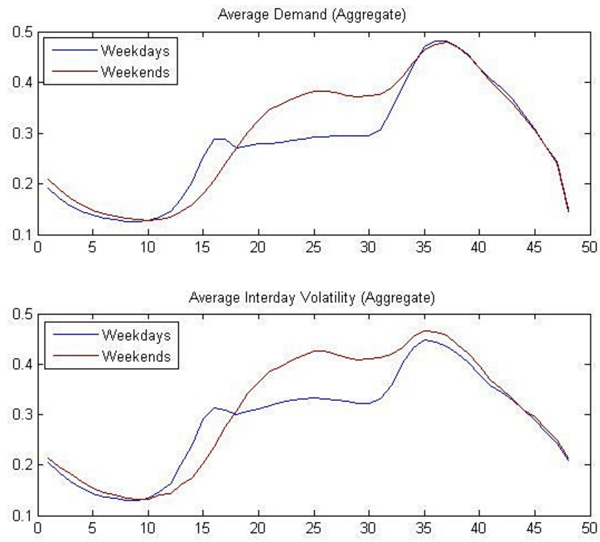

Figure 6.1: Average aggregate load and volatility for weekdays/weekends.

Next, we tried to model customer bills under the four major types of tariffs, namely flat, TOU, RTP and two-part RTP. We have split the data in weekly periods to be able to better monitor bill changes. Hence, Figures 6.3 - 6.8 illustrate the aggregate loads and volatilities observed for each week per month. The form of the consumption is similar for each week in a month, however we can see higher peaks during January, probably because of the weather conditions. This is not true for volatility though, where we can see higher deviations between different weeks. Moreover, the volatility for the weekends seems to be higher than weekdays, as consumer habits can vary over these days.

Flat rates actually correspond to forward contracts, so we needed a way to model forward prices. According to the theory, the price of a forward price, F(t), should be:

$$F(t) = E[S(t)]e^{rt} \tag{6.1}$$

where $E[S(t)]$ is the expected spot price, r the interest rate and t the time to maturity (in years). We make the simplified assumption that the

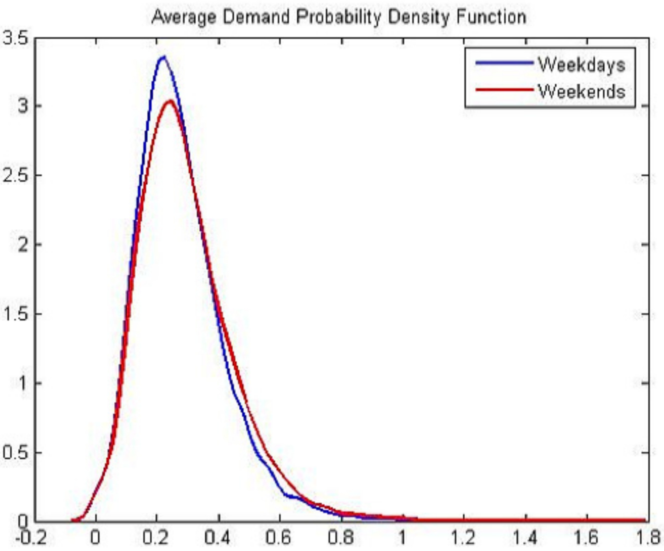

Figure 6.2: Load and volatility estimated probability density function for weekdays/weekends.

utility buys a unique forward contract for the whole period (3 months). This means that $t = 0.25$. The interest rate is assumed to be $r = 2\%$. To get the expected spot price, we have obtained the real wholesale price data for the previous year (2009) [2]. Figure 6.9 illustrates the estimated distribution of the log-prices from which we can clearly infer that prices follow the log-normal distribution, as was anticipated [80, 25]. This means that the expected wholesale price will be:

$$E[S(t)] = e^{\mu + \frac{\sigma^2}{2}} \tag{6.2}$$

where μ is the mean and σ^2 the variance of the prices. Based on this finding, Figure 6.10 shows our half-hourly expected spot prices used to calculate the flat rate. The latter should be equal to the retail forward break-even price (RF), i.e. real wholesale price with no costs of delivery incorporated [8]:

[2] http://www.electricity.org.uk

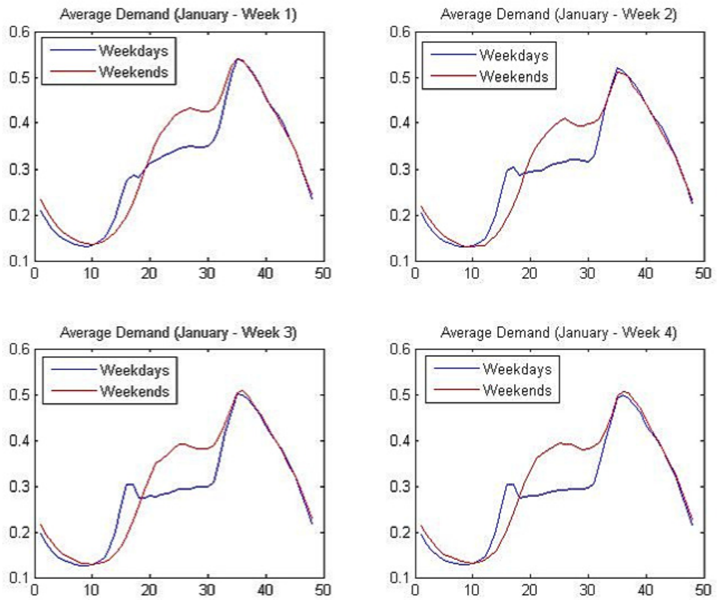

Figure 6.3: Average aggregate load for weekdays/weekends per week during January.

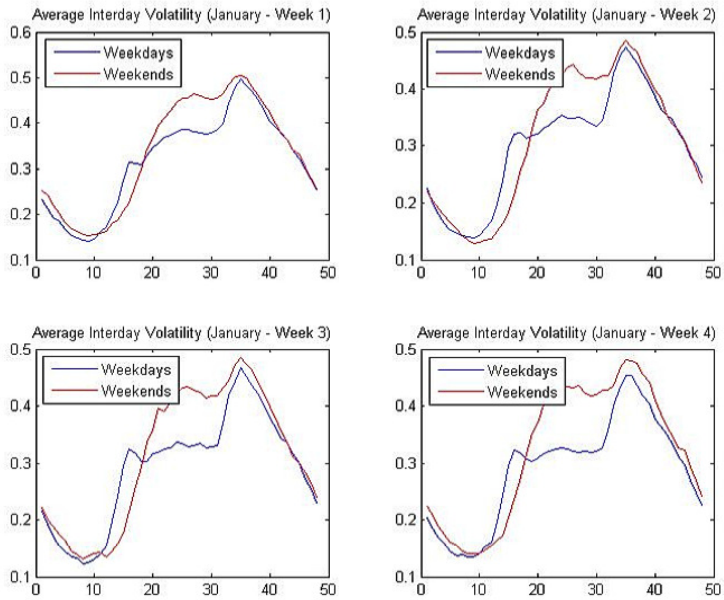

Figure 6.4: Average aggregate volatility for weekdays/weekends per week during January.

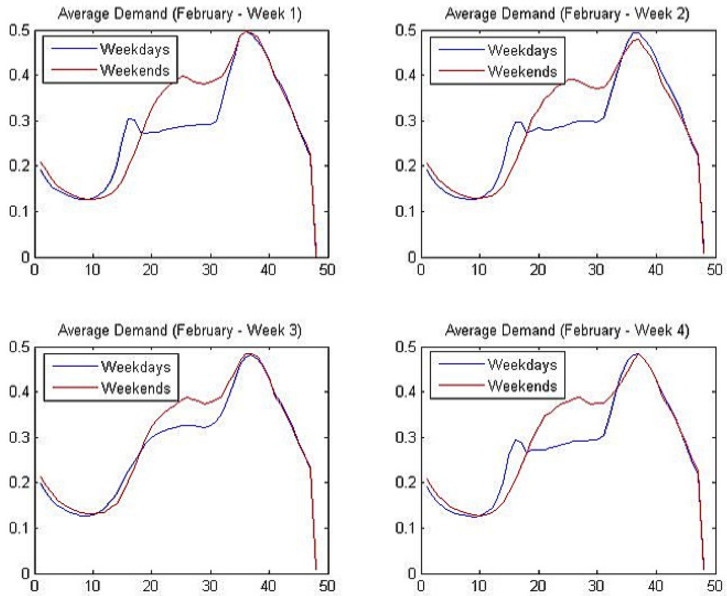

Figure 6.5: Average aggregate load for weekdays/weekends per week during February.

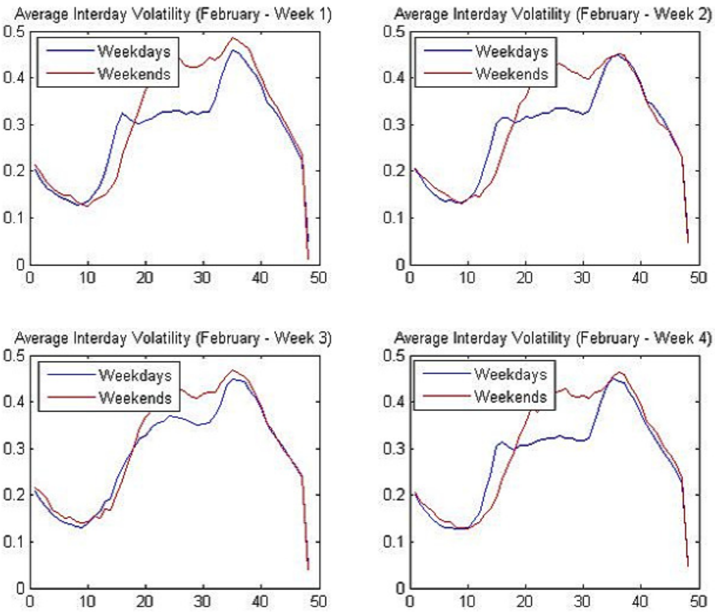

Figure 6.6: Average aggregate volatility for weekdays/weekends per week during February.

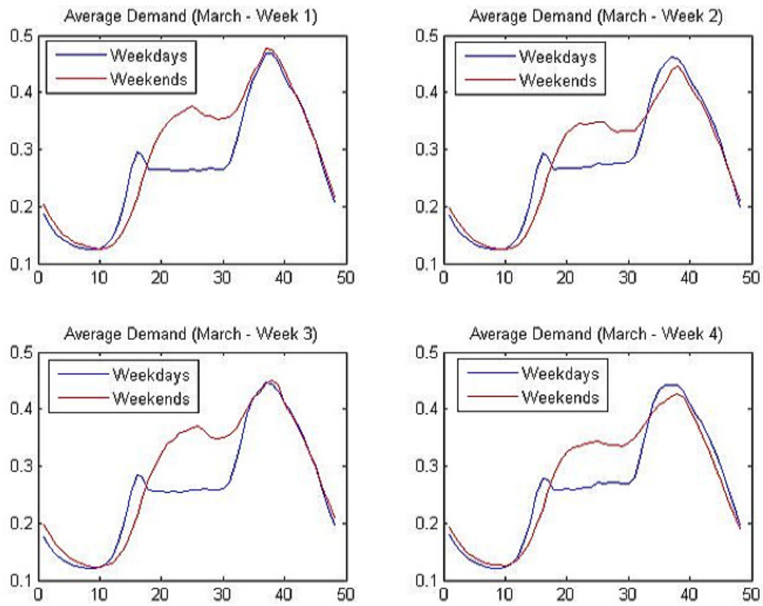

Figure 6.7: Average aggregate load for weekdays/weekends per week during March.

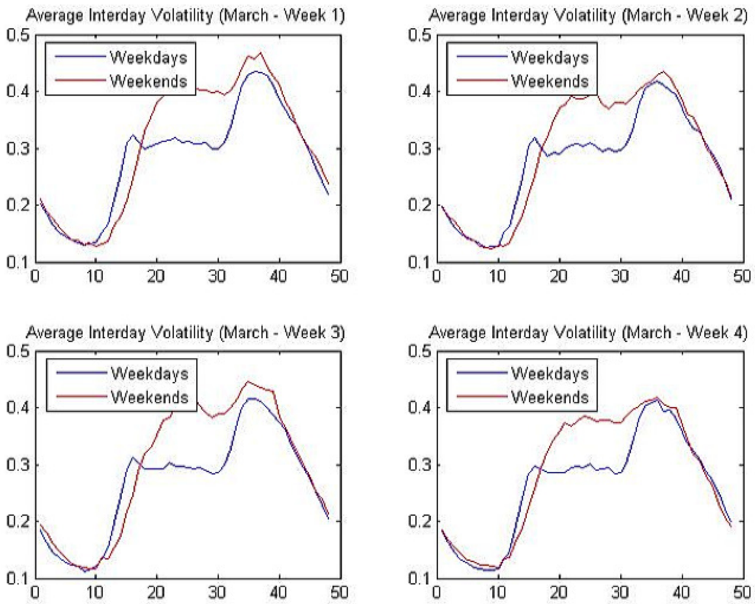

Figure 6.8: Average aggregate volatility for weekdays/weekends per week during March.

$$RF = \frac{\sum_{i=0}^{47} F(t)L(t)}{\sum_{i=0}^{47} L(t)} \tag{6.3}$$

where L(t) is the utility's average aggregate load for each half hour t. At this point we should mention that we have not incorporated transmission and distribution costs in our model, because of the complexity of this market, although these account for 30% and 10% respectively of a typical customer bill [81]. However, these rates should be identical for all types of tariffs and do not influence the quality of our results.

The corresponding TOU rate was designed such that it is revenue neutral in expectation to the customers. We consider a rate with on-peak prices starting in effect from 8 a.m. until 8 p.m. and have calculated both on-peak and off-peak prices using the aforementioned formula, which gave as an on-peak to off-peak ratio of 1.456.

RTP rates correspond to the real spot prices for the period under investigation as they were obtained from NETA website[3]. Finally, for the two-part RTP tariff, we have incorporated two types of CBL, one for weekdays and one for weekends, based on each customer's last week's average consumption data.

As Figure 6.11 depicts, each tariff bears a different level of risk for the utility. Flat (also known as flip-the-switch) rates demand an accurate long-term prediction of electricity prices and quantities consumed, whereas the RTP (spot) rate induces much lower risk. Hence, it seems appropriate to include different levels of risk premiums for each type of tariff. According to Ahmad Faruqui [9], hedging cost premiums should be an exponential function of the load volatility, price volatility as well as the correlation between demand and wholesale prices. A Monte Carlo simulation can provide us with the distribution of risk premiums (Figure 6.12) and typical values are 15%, 8% and 3% for flat, TOU and RTP tariffs respectively. Hence, we have used these values in our model.

Our results are illustrated in Figures 6.13 and 6.14 for the bills charged and corresponding bill volatilities respectively. As can be seen from the first figure, RTP tariff is better than flat and TOU rates in terms of the expenses for the customers as the tails of the PDF are much shorter. TOU rate

[3] `http://www.bmreports.com/`

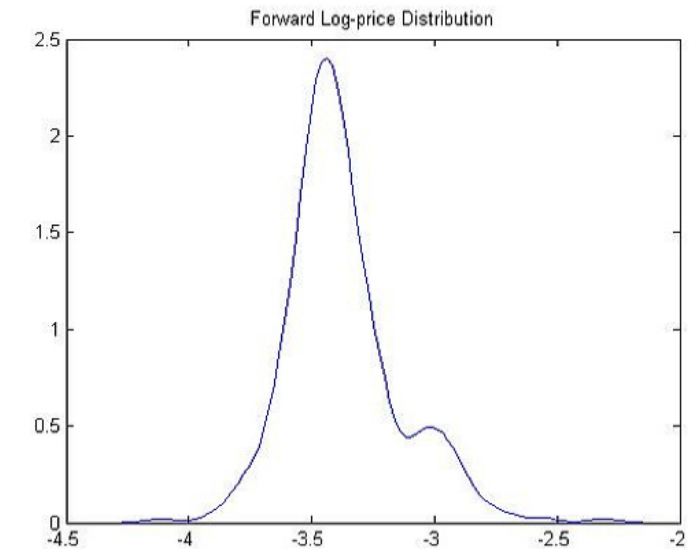

Figure 6.9: Estimated PDF of wholesale daily log-prices for 2009.

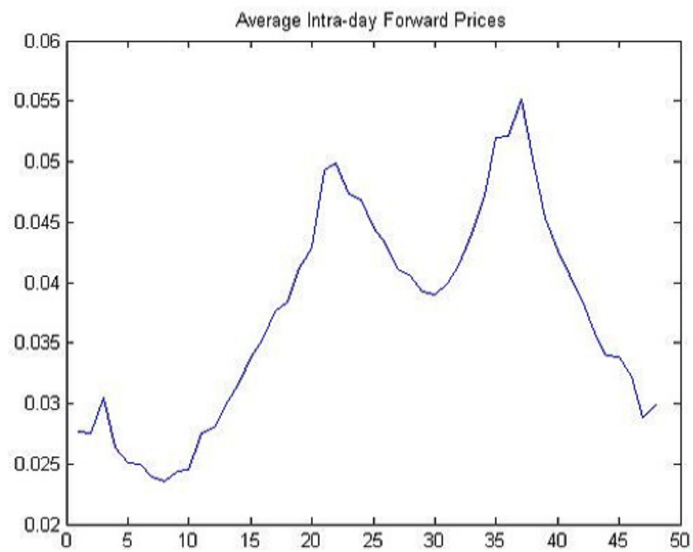

Figure 6.10: Half-hourly forward prices.

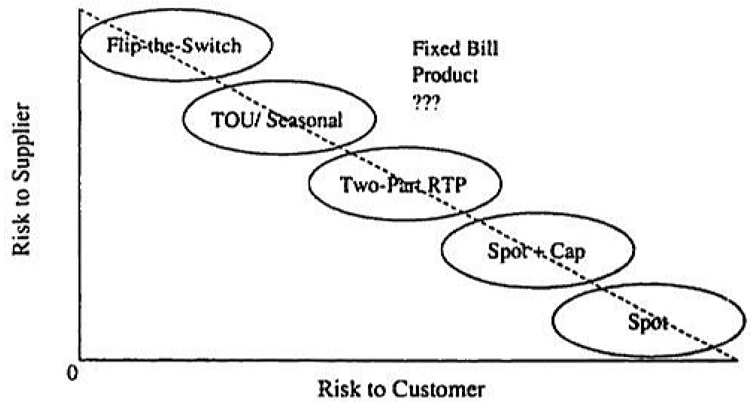

Figure 6.11: Risk-differentiated rates [8].

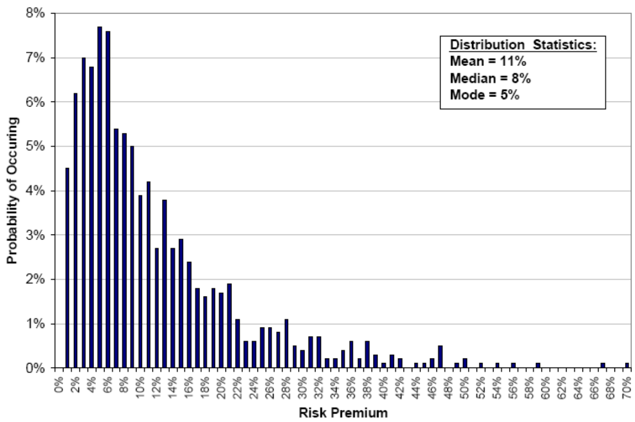

Figure 6.12: Estimated PDF of hedging premia via Monte Carlo simulation [9].

results are in turn better than flat rates, so we validate that even a modest DR application can increase bill savings. This is apparently better for the two-part RTP tariff which seems to provide benefits for the vast majority of clients. The high skewness of this distribution shows that only a small percentage with the highest volatility will pay more under this tariff, which is in accordance with our desire for social welfare. Results are also better for the volatility values where both RTP tariffs are better than TOU and flat rates. However, two-part RTP has the narrowest distribution, meaning that it is able to minimize customers' associated risk.

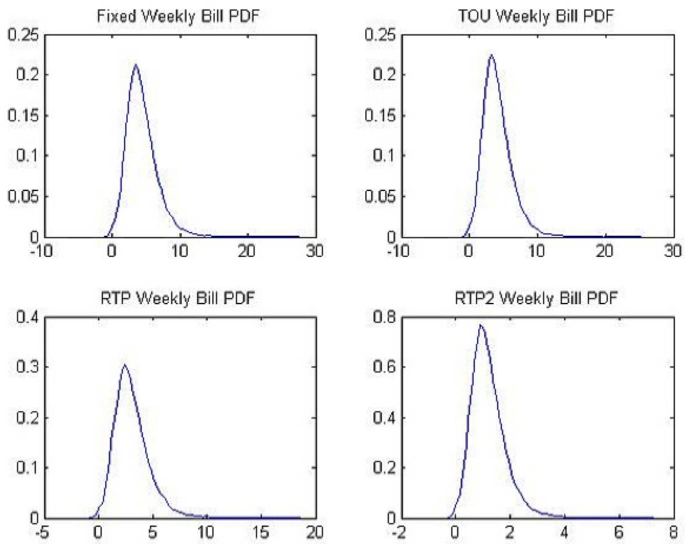

Figure 6.13: Weekly customer bill distribution.

Finally, we were interested in studying the possibility of combining flat or TOU prices with RTP ones so that profit is maximized and at the same time risk is minimized. So, we have used Markowitz framework to achieve this. Markowitz portfolio theory states that investors who wish to construct a portfolio of stocks are interested in both maximizing their profit and minimizing their risk [82]. This means that they could prefer lower profit but less volatile stocks against profitable but risky ones. More precisely, Markowitz considers an investor who has a defined initial capital and has to distribute this capital in a number, n, of provided stocks, each with an expected profit, $r_i, i = 1, ..., n$. The problem considered for a solution can be formally formed

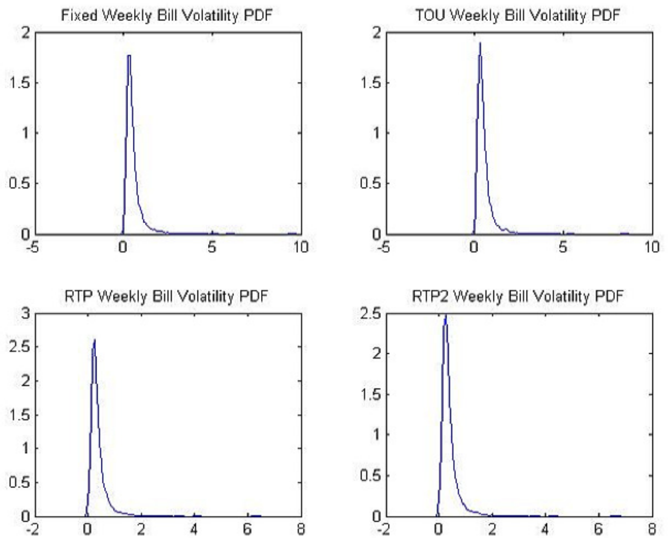

Figure 6.14: Weekly customer bill volatility distribution.

as finding the weights w_i, $i = \{1, ..., n\}$, of the following maximization problem in Linear Programming standard form:

$$max \mathbf{w}'\overline{\mathbf{r}} \tag{6.4}$$

$$s.t. \sum_{i=1}^{n} w_i = 1 \tag{6.5}$$

$$w_i \geq 0 \tag{6.6}$$

where $\overline{r}$ is the vector of expected returns, and w_i, the percentage of capital to be invested on stock i. Markowitz has proved that there is a series of portfolios that achieve this target based on customer's risk aversion, which lie in a region called the efficient frontier.

In our case, we have multiplied customers' weekly load with corresponding prices per tariff. The resulting time series can be viewed as stocks with varying degrees of profit and volatility. What we want to achieve is minimize cost (which is equivalent to maximize profit) while minimizing the risk, taking the corresponding point on Markowitz efficient frontier. To achieve this, we have utilized Matlab's frontcon function. However, low RTP volatilities and high flat-rate hedging premiums had as a result the degeneracy of the model to a single point, as the best portfolio for all customers was the one that included 100% RTP tariffs, validating once again the need for its full adoption in residential settings.

Chapter 7

Conclusions - Future Work

In the previous chapters we have made an attempt to provide an analytical description of current electricity system as well as the new Smart Grid. We have limited our attention to the trading of electricity and more specifically on how novel tariffs, currently offered in a limited number of industrial customers in the U.S. could increase DR penetration in a residential setting.

It is important to note that, although much work has been done in the AI community, the majority of the research is focused on the evolution of the system, sometimes sacrificing the accuracy of wholesale market models, which tend to be unrealistic and make the results questionable. On the other hand, economists and financial engineers develop exhaustive and accurate models that effectively capture the market dynamics but only in the short-term. It is our belief that this new system needs an interdisciplinary approach and in our work we have tried to preserve market reality to a satisfying extense.

Our results depict that RTP and especially two-part RTP tariff is an effective pricing mechanism. So, given that the government promotes smart meter installation programs, alleviating the problems of installation cost, it is our belief that this rate will soon become widely used.

As a future work we would first like to investigate how customers having onsite generation facilities could optimally respond to each type of RTP tariff so that both their profit is maximized and bill volatility is minimized. Moreover, customer strategies on how to select the most appropriate price protection product and optimize their desired percentage of CBL to hedge their risk are definitely one of our first priorities.

Customers exhibit two main types of volatility, namely an intra-day and an inter-day one. The former refers to their daily consumption pattern where different peaks can be observed and lead to extremely high spot prices. The inter-day volatility refers to their load deviations between different days. Hence, a customer might have a desirable flat load profile but can be quite unpredictable, thus contributing to the volumetric risk that the utility faces, which is quite important as the majority of trading is performed via long-term forward contracts. A proper, fair pricing mechanism for this type of risk should be designed and it would be intruiguing to see how customers would respond to this tariff, creating a coevolving population of customers and utilities. Finally, a realistic modeling of transmission and distribution markets would be an important addition to our findings.

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