HOUSEHOLD ELECTRICITY COST REDUCTION

Electricity cost reduction through time-varying pricing with game theoretical scheduling for household consumers

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Abstract

Electricity cost reduction for household consumers is researched in this thesis through real-time electricity pricing scheme with game-theoretical demand-side management and later, implications of home electricity generation is researched economically. Four different methodologies are followed during this thesis. These methodologies are shortly described:

The first one is statistical bottom-up modelling of electricity demand profiles. Before starting with research questions, it is important to build electricity demand profiles of households. Two-week demand profile of ten households for every season is generated by using bottom-up electricity demand profile simulation program based on (Richardson I. , Thomson, Infield, & Clifford, 2010).

Then, fixed pricing scheme is compared to time-varying pricing scheme by a simple micro-economic theory that the electricity market behaves in competition and in competitive markets, firms are free to set price and quantity; if a firm sets a price above the prevailing market price, its product will not be purchased; if it sets its price below the market price, its profits will be needlessly lost, since it can get as many customers as it wants by pricing at the market price (Varian, 1992). In fixed pricing scheme, there will be a single retail market price regardless of how much end-users consume electricity. When the retail price of electricity does not vary over time, a wholesale seller's attempt to exercise wholesale market power and raise wholesale prices has no short-run impact on quantity since end-use customers do not see a change in the retail price. With time-varying prices demand changes are reflected in the wholesale price, an attempt to raise wholesale prices will impact retail prices and thus reduce the quantity of power that customers demand. This customer response reduces the profitability of raising wholesale prices and, thus, discourages the exercise of market power (Borenstein, 2005). Given the microeconomic theory, a new real-time pricing scheme is suggested for the end-users.

Real-time pricing shows electricity prices for every hour of the day. End-users have shiftable appliances, which can be turned on by electricity scheduler. If all the consumers move to off-peak price hours with similar pattern, when the electricity prices are lower, there could be a new peak demand. This new peak demand, which is called "re-bound effect", will increase the electricity price for next hours. Scheduling consumption of end-users with game theoretical model prevents "re-bound effect". A non-cooperative game theoretical model to schedule "shiftable appliances" of consumers is suggested.

At last, payback period of PV solar panels is compared in case of fixed pricing and real-time pricing. This comparison shows us how the real-time pricing can help in PV solar panels market.

Preface

Energy is the most important source for human civilization. This source is exposed to the risks of depletion. As a candidate of a financial engineer, I motivate myself to work on the problems of energy sector, so then I may contribute to humanity. I studied Bachelor of Science Mechanical Engineering Energy Specialization. My bachelor thesis was titled 'Financial Analysis of Power Plants and Effects of Growing Carbon Markets on the Energy Sector'. Throughout my bachelor thesis project, I had to make assumptions for interest rates and fuel prices. I wanted to replace these assumptions with more scientific approach and this lead me into forecasting and price modeling. My interest in forecasting and price modeling shaped my master applications and I chose to study Master of Science Financial Engineering and Management.

University of Twente, with its motto 'de ondernemende universiteit', supports versatile and liberal engineering education. This support gave me a privilege to to choose courses from Sustainable Energy and Management Master of Science program as well. This versatile education system brought me new ideas about the energy finance. I have used financial engineering tools to solve the problems in household electricity consumption such as statistical modeling for generating realistic user electricity demand profiles, econometric tools to forecast next hour electricity prices, microeconomics to build a new pricing scheme and game theory to optimize consumer wealth.

All this knowledge, I owe to University of Twente and its inspiring professors:

I would like to thank Dr. M. J. Arentsen to support my ideas in the very beginning of my thesis. His expertise in the energy policy has enlightened me to see where retail electricity markets are moving.

I would like to thank V. Bakker, who has received his PhD degree on control strategy for smart grids. His PhD defense enlightened me to see which latest technology improvements made in energy distribution. Moreover he has supported me with his valuable feedback throughout this project.

And last, I would like to thank my study coordinator, Dr. B. Roorda, who has supported me throughout my studies and thesis with his expertise in Financial Engineering.

Best regards,
Can Arslan

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1. Introduction

The global energy market is exposed to the risk of increasing energy resource usage, scarcity of energy resources and growing environmental concerns. These risks are causing governmental and non-governmental bodies to take new actions in generation, transmission, distribution and consumption of energy. These actions aim to increase the efficiency of energy, thus reduce the costliness of energy and reduce the negative impact on environment.

Most recent of developments to increase the efficiency of energy consumption are smart grid applications and demand-side management, which are frequently used in generation, transmission, and distribution. The smart grid is the collection of all technologies, concepts, topologies, and approaches that allow the hierarchies of generation, transmission, and distribution to be replaced with an end-to-end, organically intelligent, fully integrated environment where the business processes, objectives, and needs of all stakeholders are supported by the efficient exchange of data, services, and transactions [32]. Smart grid technology enables systematic communication between suppliers and consumers; this communication helps to optimize energy production and consumption. Demand Side Management (DSM) is a portfolio of measures to improve the energy system at the side of consumption. It ranges from improving energy efficiency by using better materials, over smart energy tariffs with incentives for certain consumption patterns, up to sophisticated real-time control of distributed energy resources [59].

Household electricity market is responsible for some 24% of electricity consumption in the Netherlands. Household electricity demand is in increasing trend in the Netherlands over 20 years, this is because of increasing use of household appliances such as freezers, clothes driers and dishwashers and increasing use of PCs has also played an important role in the electricity demand of households. The cost of energy has risen steeply over the past years as a result of increasing oil prices: rates for gas are linked to the price of oil, and since gas is also a major source of fuel for generating electricity; this has resulted in higher rates for electricity too [27]. Recent increasing trend of electricity costs force household consumers to search for ways to decrease their electricity costs. The research presented in this thesis aims to reduce electricity cost of households through using smart grid technology and DSM methods.

1.1 Problem statement: Current State and Desired Situation

While minimising their electricity cost, household electricity consumers want to maintain their convenience. This can be possible by offering different *demand response incentives* to the retail market, which help household consumers to benefit maximum from shifting their demand. Moreover household consumers need to *schedule their consumption shifts* cooperatively not to cause new demand peaks, which results in new price peaks.

After a new demand response incentive and electricity consumption scheduling is applied, *distributed generation technologies* is suggested to be invested for household consumers to be more independent from the grid prices, investments to these technologies must be paid back in reasonable periods. Current situation of these three offered solutions are given below:

Demand Response Incentive:
Currently household consumers are either charged by single-pricing contracts, which does not motivate consumers to shift their demand, or they are charged by multi-part tariff contract, which are two level, day and night time, electricity prices. In the day and night time electricity pricing, household consumers are also exposed to strict prices, which does not motivate them to shift their demand. If household consumers want to benefit more from shifting their demand, time-varying price incentives have to be followed. This solution is explained detailed in Chapter 4.

Electricity Consumption Scheduling:
Market-based operation and deregulation of the electricity industry places consumers in the centre of the decision-making process. Clearly, development of Demand-Side Management (DSM) will provide choice to consumers regarding usage of electricity, however DSM has not yet been fully integrated into the operation of electricity markets. Most of the existing demand-side management programs available today focus primarily on the interactions between a utility company and its customers. Smart grid infrastructure and demand-side management will cause domestic-users to behave in a certain way of electricity consumption scheduling game, where the players are the users and their strategies are the daily schedules of their household appliances and loads. If these players shift their electricity consumption at the same time, there will be new peak electricity consumption occurring, this is called “re-bound effect”. So then the players have to behave in a cooperative way to keep demand stable. This could be achieved by electricity consumption scheduling with a game theoretical approach. This solution is explained detailed in Chapter 5.

Distributed Generation
The current electricity law allows renewable domestic generators as well as hybrid generators that make use of fossil fuels to feed up to 3000 kWh into the electricity grid per connection per year. This allows those kWh to be subtracted from the used kWh and thereby receive a full value of the electricity. Since grid operators have to take the delivery of feed-in power, investing in domestic-scale distributed generation technologies such as PV solar panels. Moreover The Netherlands is obliged to meet the renewable energy criteria by European Union, which is 14% renewables in total energy consumption target in 2020 (Directive 2009/28/EC, Annex I), this target shapes the policies, which support renewable energy programmes. The increase in investment of domestic-scale distributed generation technologies bring new debate in economical feasibility of these investments, which is shown in Chapter 6.

1.2 Goal

Main goal of this research is to reduce the electricity cost of household consumers while maintaining the same level of comfort. Two different methods are proposed to achieve this goal.

First, time-varying pricing incentive is suggested for household users, which will give more independence for household users to schedule their electricity demand, thus more cost efficiency is obtained. Moreover a game theoretical model for group of consumers is built to optimise best scheduling for "shiftable" appliances, so then "re-bound effect" will be prevented.

Second, investment of photovoltaic solar panels is suggested in the proposed case of electricity scheduling game under time-varying prices. Since the household consumers are more cost efficient in the proposed case, it is economically more advantageous to invest then in current case with single pricing scheme.

1.3 Research Question

Research question is formulated to meet the research targets as following:
"How can household consumers benefit economically from time-varying pricing schemes with game-theoretic electricity consumption scheduling?"

Sub-questions
These sub-questions are followed to answer research question:

A. How can electricity-pricing incentive be built to motivate household consumers to schedule their "shiftable" appliances?

B. How can a game theoretic framework be used for electricity scheduling to minimise electricity costs of household consumers?

C. How are photovoltaic solar panels investments economically feasible in time varying price incentive with electricity scheduling game situation?

1.4 Research Approach

DSM includes conservation and energy efficiency programs; reducing consumption and shifting consumption are the main tools. Reducing the consumption can be achieved through encouraging user awareness and building energy efficient buildings. However there is also need to shift the high power household appliances to off-peak hours to reduce electricity costs. In this thesis project, price-based rates demand response programme has been offered so then the households can make more benefits of shifting their loads in time-varying prices.

Electricity consumption profiles of households are built by using a bottom-up methodology based on a previous research. These profiles are used as starting point of the research to apply time-varying pricing schemes. Time-varying pricing schemes is summarised by literature research. Depending on these research results, a retail-pricing model is proposed. In retail-pricing model, next hour electricity prices are forecasted by using a time-series statistical model proposed by previous literature researches. Data analysis of APX-Endex takes place as a part of this model.

Moreover, a scenario, where several consumers share a source of electricity, is considered. If all the consumers shift their load at the same time, there will be a new peak demand occurring, which is called 'rebound effect'. As a solution, each one of the consumers is equipped with an automatic electricity consumption scheduler (ECS). The smart meters with ECS functions interact automatically by running a distributed algorithm to find optimal electricity consumption schedule for each user. The optimization problem is to minimise the electricity cost in the system. This optimization problem can be expressed in a game-theoretic analysis, which is a mathematical modelling of users' interaction.

The electricity consumption game among the participating users, who share the same electricity source, gives the optimal solution of a system-wide optimization problem. Once the optimization problem is solved, new electricity cost is calculated. Payback period of Solar Photovoltaic Power systems in new electricity cost regime is compared to conventional electricity cost regime to prove the change in economical feasibility of these investments.

1.5 Structure of Report

Chapter 2: Background
Electricity cost of household consumers in the Netherlands is described. Methods to minimise electricity cost are listed: Smart Grid, Demand-Side Management and Investment in Micro-Generation technologies. These keywords are explained in detail. Driving factors for micro-generation and smart grid are shown and current global energy policies are summarised.

Chapter 3: Electricity Consumption Profiles
Household Electricity Demand is explained. Household electricity consumption profile is built using bottom-top method. "Shiftable" and "non-shiftable" appliances are listed.

Chapter 4: Proposal of A Time-Varying Pricing Scheme
Retail electricity pricing schemes are shown. Time-varying pricing schemes are explained. Electricity price forecasting is needed for the proposed electricity pricing model, so forecasting is shown and proposed model is explained

Chapter 5: Proposal of An Electricity Consumption Scheduling
Consumption scheduling is obtained by using game theoretical models. The literature is summarised and proposed game theoretical model is shown.

Chapter 6: Investment Performance of Photovoltaic Solar Panels
Domestic-scale distributed generation applications are observed. Pay-back period of PV solar panels are calculated in both current situation and proposed situation. Results are discussed.

Chapter 7: Conclusions
The report is summarised, the feasibility studies are compared and the results are discussed. Moreover, future research proposals are given.

2. Background

Electricity market is affected by increasing petroleum and natural gas prices globally. On the top of these increasing prices, energy demand trend is also increasing globally. All these are affecting the wholesale and retail electricity markets, which are causing increasing electricity prices for household consumers. This argument is going to be explained in details in following sections. In this environment, household consumers are looking for using electricity more cost-efficiently. This thesis is proposing an electricity consumption-scheduling (ECS) algorithm for households in case of time-varying prices and comparing results when photovoltaic solar panels are built in households.

Before research question is answered, it is important to know how ECS technology is made possible today. Smart Grid system enables customers to communicate with utilities better. Consumers can follow the peak and off-peak demand on the grid and plan their consumption accordingly. With the help of smart grids, demand-side management (DSM) methods can be applied in households. DSM is a known method for many years to manage electricity consumption scheduling. In this chapter, smart grid technology and DSM is explained in detail and the DSM method used in this thesis is summarised. Later, a recent trend in domestic energy sector called micro-generation is explained shortly.

In the next sections electricity cost of households, smart grid technology, demand-side management and micro-generation is reviewed from the literature.

2.1 Electricity Cost of Household Consumers

Household electricity demand is in increasing trend in the Netherlands over 20 years (1990-2010) as it is shown on Figure 2.1. The growth up to 2008 follows increasing use of household appliances such as freezers, clothes driers and dishwashers and increasing use of PCs has also played an important role. Factors that are thought to have played a role in the apparent stabilisation of electricity consumption after 2008 are, the market penetration of appliances such as freezers, clothes driers and dishwashers levelled off, and household appliances, which typically use large amounts of electricity were replaced with more energy efficient models [27].

Increasing number of electric vehicle (EV) and plug-in hybrid electric vehicle (PHEV) users are expected to add on more household electricity demand in next years.

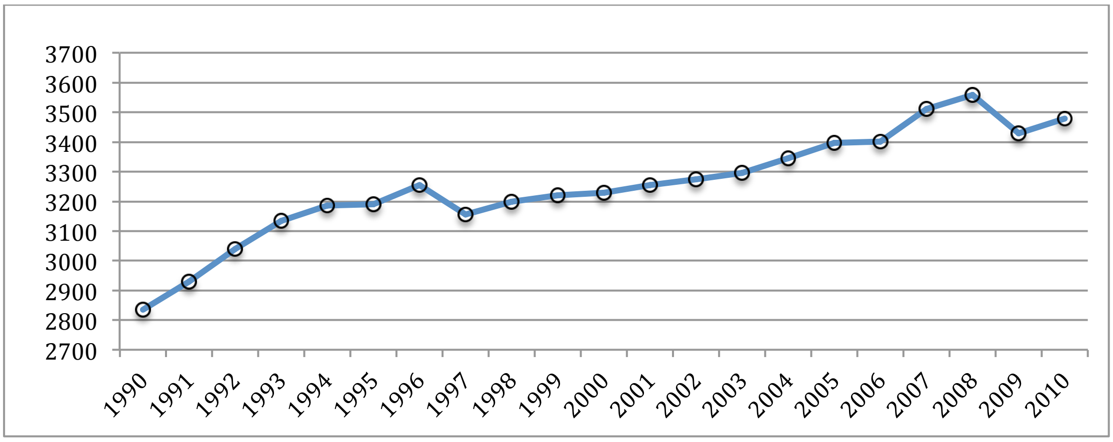


Figure 2.1 Average Household Electricity Consumption (kWh/year) from 1990-2010 (Energie Nederland, 2012)

Household electricity prices mainly depend on demand and marginal production costs of suppliers. Electricity demand depends on mainly variables such as weather conditions, seasonal conditions and marginal production costs of suppliers mainly variables such as petroleum and natural gas commodity prices [85]. The cost of energy has risen steeply over the past years as a result of increasing oil prices: rates for gas are linked to the price of oil, and since gas is also a major source of fuel for generating electricity; this has resulted in higher rates for electricity too [27].

Household electricity cost is increasing as the demand and electricity prices are increasing. Households can decrease their electricity cost by getting more independent in electricity supply; this can be possible by investing in photovoltaic solar panels. Moreover, households can choose different pricing incentive for their electricity consumption and use demand-side management applications by using smart grids; which enables them to shift their electricity consumption of appliances from peak hours to off-peak hours.

As it is seen from the Figure 2.2, consumers find energy prices increasingly more expensive [57].

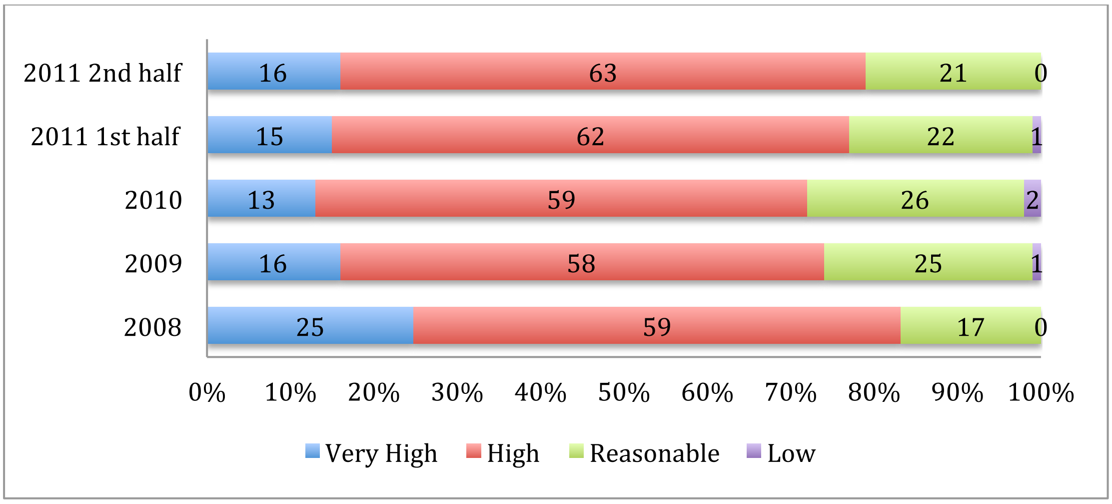


Figure 2.2 Household Consumer's Perception of Energy Prices (Office of Energy Regulation, 2012)

2.2 Smart Grids

In this section, smart grids are introduced to the reader. It is important to emphasise the technological development of the electricity grids in this thesis, since these developments make the modelling of the suggested demand-side management methods possible to implement.

2.2.1 Smart Grids: History and Definition

History

The electricity grid as we know it today has been designed 50-100 years ago and still works via the same principles. Electricity was produced at central places and transported one-way downwards to the customers [53]. As you can see from the Figure 2.3, the conventional electricity grid is a strictly hierarchical system in which central generation (power plants) at the top of the chain ensure power delivery to customers' loads at the bottom of the chain.

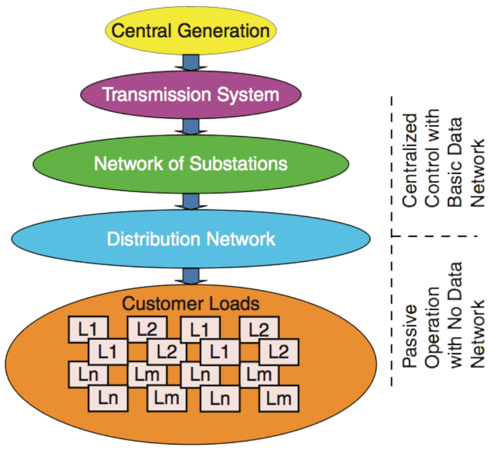


Figure 2.3 Sketch of the conventional grid structure [32]

In conventional grid structure, power plants do not have real-time information about the service parameters of the customer loads. The grid is therefore engineered for maximum anticipated peak demand across its aggregated load. And since this peak demand is an infrequent occurrence, the system is inherently inefficient. Moreover, an unprecedented rise in demand for electrical power, coupled with lagging investments in the electrical power infrastructure, has decreased system stability. With the safe margins exhausted, any unforeseen surge in demand or anomalies across the distribution network causing component failures can trigger blackouts [32].

The conventional grid was designed decades ago with different design principles, and environmental and societal circumstances. Back then; fossil fuels were cheap and abundant. Although nowadays renewables have an increasing share in the energy mix, fossil fuels are still dominant [7]. For example, the energy mix of the Netherlands in 2010 shows that 77.1% of the electricity production was fuelled by fossil fuels [27]. But the circumstances are changing: fossil fuels are becoming expensive and are produced by political less stable countries. Besides the economical and political problems in harvesting these fossil fuels, most of the fossil fuels are consumed with a very low efficiency.

The generation efficiency of power stations varies between around 35% (older coal stations) to over 50% (modern combined cycle stations), averaging to about 39%. When transmission and distribution losses are considered, the average overall efficiency of the system drops to 35% [21]. Fossil fuelled power plants, with their low overall efficiency, cause environmental problems emitting green house gases in air. Today, there is a general consensus on the impacts of human activities on global climate change. The interest related to climate issues is growing publicly and the debate now focuses on the actions that need to be undertaken to avoid damages. These actions force countries to move on sustainable energy sources. These sustainable energy sources are connected to the grid different than conventional energy sources.

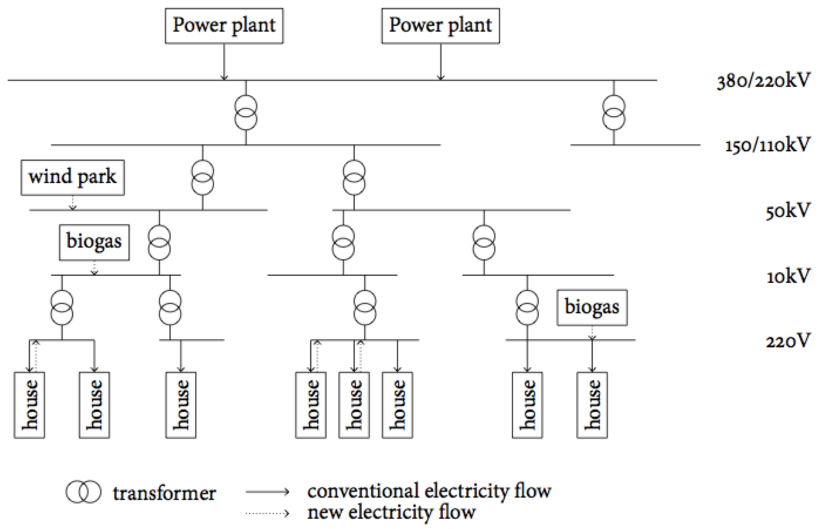


Figure 2.4 Overview of the Dutch electricity network [53]

As you can see in Figure 2.5, wind park and biogas are given as examples of sustainable energy sources, moreover a new electricity flow from houses to grid is introduced. Addition of these sustainable energy resources requires new developments in grid technology. A change towards another supply chain with more sustainable energy production via continuous management of production, transportation and consumption requires a so-called 'Smart Grid'.

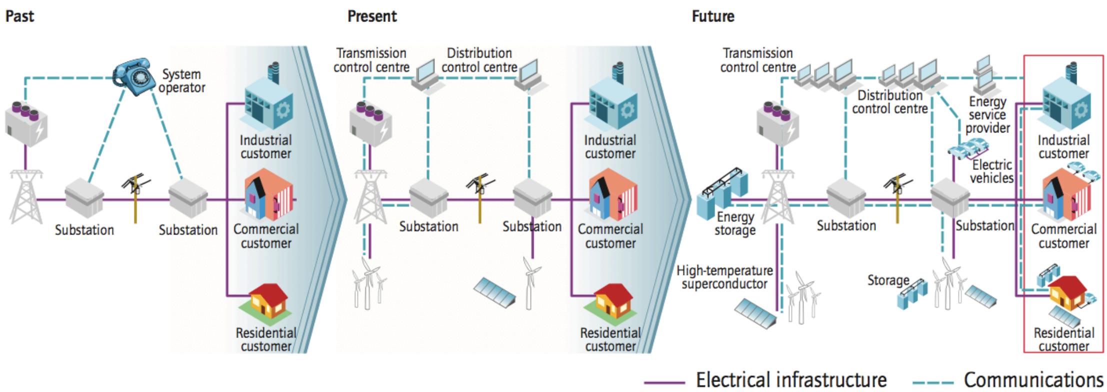


Figure 2.5 Evolution of grids [39]

Definition
A smart grid is an electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demands of end-users. Smart grids coordinate the needs and capabilities of all generators, grid operators, end-users and electricity market stakeholders to operate all parts of the system as efficiently as possible, minimising costs and environmental impacts while maximising system reliability, resilience and stability [39].

2.2.2 Smart Grids: Technology and Application

The smart grid technology areas cover the entire grid, from generation through transmission and distribution to various types of electricity consumers. Some of the technologies are actively being deployed and are considered mature in both their development and application, while others require further development and demonstration. A fully optimised electricity system will deploy all the technology areas in Figure 2.7. However, not all technology areas need to be installed to increase the "smartness" of the grid [39]. In this thesis, electricity consumption scheduler (ECS) is used, which is a customer-side smart grid technology shown in Figure 2.6.

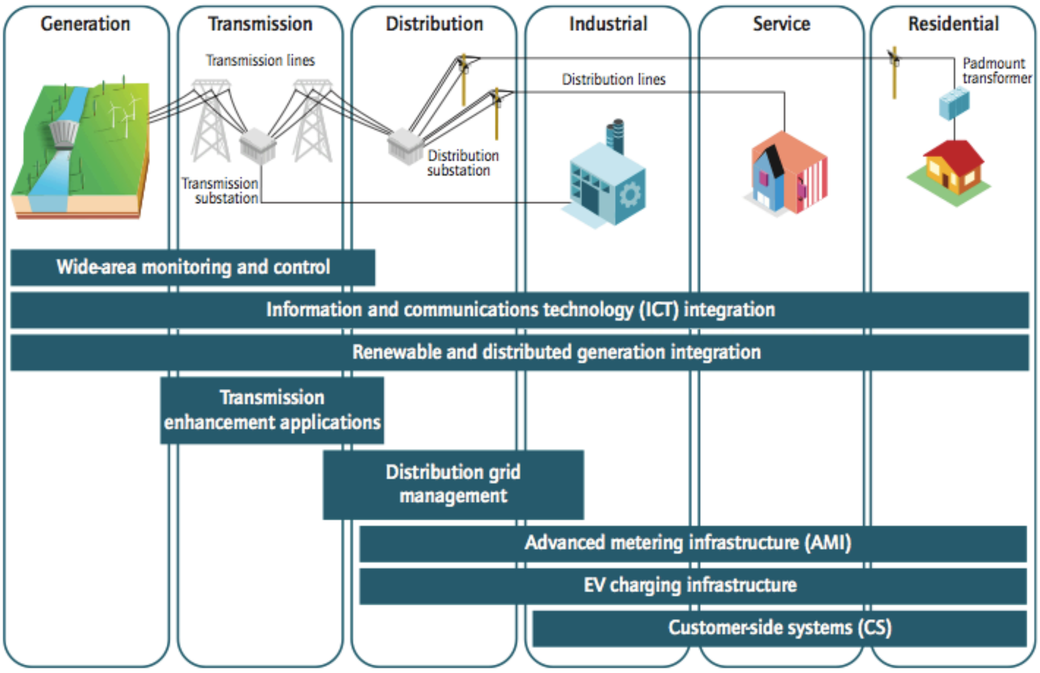


Figure 2.6 Smart Grid Technology Areas [39]

The smart grid is the collection of all technologies, concepts, topologies, and approaches that allow the hierarchies of generation, transmission, and distribution to be replaced with an end-to-end, organically intelligent, fully integrated environment where the business processes, objectives, and needs of all stakeholders are supported by the efficient exchange of data, services, and transactions. A smart grid is therefore defined as a grid that accommodates a wide variety of generation options. It empowers consumers to interact with the energy management system to adjust their energy use and reduce their energy costs. A smart grid is also a self-healing system. It predicts looming failures and takes corrective action to avoid or mitigate system problems. A smart grid uses IT to continually optimise the use of its capital assets while minimising operational and maintenance costs [32].

Here, it is recommended to take a look at the evolution of smart grid technology and remember all the technologies and concepts used by utilities before. As Figure 2.7 shows, the metering side of the distribution system has been the focus of most recent infrastructure investments. The earlier projects in this sector saw the introduction of automated meter reading (AMR) systems in the distribution network. AMR lets utilities read the consumption records, alarms, and status from customers' premises remotely.

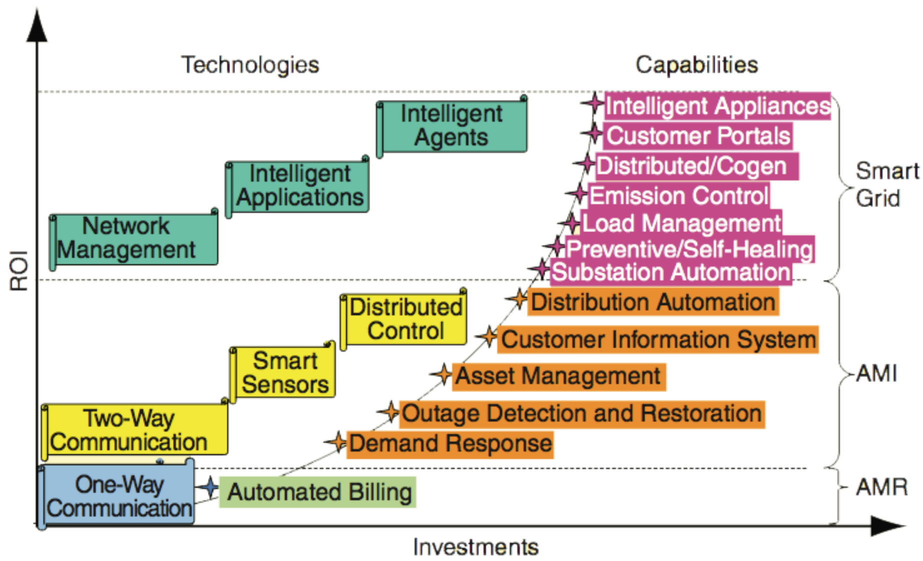


Figure 2.7 The evolution of Smart Grid [32]

Due to its one-way communication system, AMR's capability is restricted to reading meter data. It does not let utilities take corrective action based on the information received from the meters. For example, a sudden decrease in demand cannot be feed back to the utility on time, which cause the waste of energy production. Consequently, AMR technology was short-lived.

Rather than investing in AMR, utilities across the world moved towards advanced metering infrastructure (AMI). AMI provides utilities with a two-way communication system to the meter, as well as the ability to modify customers' service-level parameters. Through AMI, utilities can meet their basic targets for load management and revenue protection. They do not only get instantaneous information about individual and aggregated demand, but they also impose certain caps on consumption, as well as enact various revenue models to control their costs.

As the next logical step, the smart grid needs to leverage the AMI infrastructure and implement its distributed command and control strategies over the AMI backbone. The pervasive control and intelligence that embodies the smart grid has to reside across all geographies, components, and functions of the system.

Distinguishing these three elements is significant, as it determines the topology of the smart grid and its constituent components [32].

2.2.3 Driving factors for Smart Grids

In [40], five major driving factors for distributed generation are listed as follows; market liberalisation, developments in distributed generation technology, constraints on the construction of new transmission lines, increased customer demand for highly reliable electricity and concerns about climate change. These factors show similarities with driving factors for Smart Grids, [30] lists three major factors as follows; internal market, security of supply and environment.

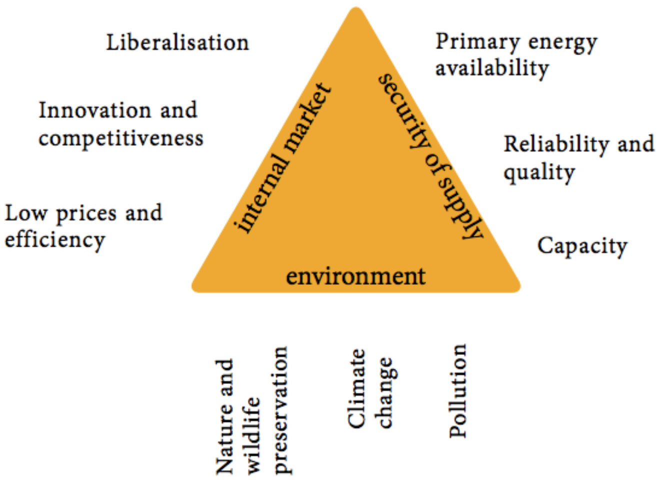


Figure 2.8 Schematic of the driving factors for a Smart Grid [30]

The European Internal Market:

Liberalisation of energy markets and unbundling of former vertically integrated utilities has led to a huge number of new actors at all stages of the energy value chain. Grid operators, for example, have to deal with a multitude of supply companies in their network area. At the same time, energy exchange markets such as the European Energy Exchange (EEX) in Leipzig, Amsterdam Power Exchange (APX-ENDEX), allow the trading of electricity internationally. The consequence of these developments is a multiplication of processes and operations compared to an integrated management in pre-liberalisation times. Information must flow across companies' borders and communication between parties involved in the electricity system becomes more and more important [88].

Security and Quality of Supply:

Modern society depends critically on a secure supply of energy. Countries without adequate reserves of fossil fuels are facing increasing concerns for primary energy availability. Furthermore, the ageing infrastructure of Europe's electricity transmission and distribution networks is increasingly threatening security, reliability and quality of supply [30]. This is possible by smart grids, the following example shows why.

Liberalised markets can be risky to hold a high reliability level, because of the incentives for cost-effectiveness that come from the introduction of competition in generation and from the re-regulation of the network companies, it might be that reliability levels will decrease [62]. Two solutions are suggested by Distributed Generation technology to come over reliability problem; back up systems and fuel cells. In Figure 2.5, it is shown that the interconnectivity of distributed generation technology such as electricity storages, which can be back up systems and fuel cells, are possible by smart grids.

The Environment:
Increase in distributed generation is mainly driven by the flourishing renewable energy sector. The Dutch green electricity policies have evolved since the oil crisis in 1973. Directly after the first oil crisis, the government took action in promoting research and development of renewable energy. Then starting by 1990, [81] suggests three phases in policy development: phase one was voluntary targets, the government negotiated voluntary agreements with the energy distribution sector in early 1990s; phase two was promotion of demand, the government introduced a regulatory energy tax in 1996, this tax support is followed by the liberalisation of the green consumer market in 2001; phase three is promotion of production, this policy was called "environmental quality of electricity production" implemented in 2003. Moreover the government is promoting the production of renewable energy via the Sustainable Energy Incentive Scheme Plus (SDE+) recently. Under SDE+, the annual budget is no longer distributed across the different technologies in advance; rather, the different technologies have to compete under a single budgetary ceiling. Priority for subsidies is given to the cheapest technologies, and the scheme therefore contributes to achieving the 2020 target as cost-effectively as possible. Subsidies are available under SDE+ not just for the production of renewable electricity, but also for renewable heating and green gas, both of which will also make an effective contribution to the 14% renewables in total energy consumption target (Directive 2009/28/EC, Annex I) [50].

All these policies increase the number of renewable energy investments in the Netherlands. This increases the ratio of distributed generation, which is connected to grid on medium voltage level as seen on Figure 2.4. The feed-in of many small distributed sites can lead to a power flow reversion and thus change the original power flow direction, which runs from higher to lower voltage levels. At the same time, there is a high volatility in the feed-in of wind and solar power. This can lead to situations where the grid is no longer efficiently controllable within the limits of its current infrastructure. For example, in times of overload, load rejection may result in a complete cut-off of single wind turbines that deliver carbon-free power. In such moments the grid has to deal with conditions it was not built for. A reasonable steering without the help of information and communication technologies (ICT) is difficult in this situation, especially in distribution grids [88].

2.3 Demand-Side Management

For many years, Demand-Side Management (DSM) has been regarded as the "Holy Grail" of efficient power generation. DSM is basically perceived as the solution to a classical dimensioning problem, namely the fact that the current power generation and distribution infrastructure is designed to accommodate peak and not average demand. Because the demand fluctuates substantially over a daily cycle, a sizeable chunk of the system capacity is effectively wasted [70].

Demand Side Management (DSM) is a portfolio of measures to improve the energy system at the side of consumption. It ranges from improving energy efficiency by using better materials, over smart energy tariffs with incentives for certain consumption patterns, up to sophisticated real-time control of distributed energy resources [59].

According to [59], depending on the timing and the impact of the applied measures on the customer process, DSM can be categorized into the following:
a) Energy Efficiency (EE).
b) Time of Use (TOU).
c) Demand Response (DR).
d) Spinning Reserve (SR).

In this thesis project, demand response programmes are applied. The following chapter explains demand response programmes in detail.

2.3.1 Demand Response

Demand Response (DR) can be defined as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [79]. DR includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption [41]. Demand Response can be divided into two groups Incentive-Based DR and Price-Based DR:

a) Incentive-Based DR: These programs give participating customers incentives to reduce load that are separate from, or additional to, those customers' retail electricity rate, which may be fixed (based on average costs) or time-varying. The incentives may be in the form of explicit bill credits or payments for pre-contracted or measured load reductions. Customer enrolment and response are voluntary, although some demand response programs levy penalties on customers that enrol but fail to respond or fulfil contractual commitments when events are declared. In order to determine the magnitude of the demand reductions for which consumers will be paid, demand response programs typically specify a method for establishing customers' baseline energy consumption (or firm service) level against which their demand reductions are measured [79].

b) Price-Based Rates DR: These programs give customers time-varying rates that reflect the value and cost of electricity in different time periods. Armed with this information, customers tend to use less electricity at times when electricity prices are high [79]. There are three main price-based rates demand response programmes: Time-of-use rates, real-time pricing and critical peak pricing. These programmes are explained in detail in Chapter 4.

2.3.2 Energy Consumption Scheduling

Energy Consumption Scheduling is also a method of demand-side management. This management method suggests households to schedule their "shiftable" loads in order to utility and consumer self benefits.

[51] uses energy consumption scheduling to minimise peak-to-average ratio for the benefit of utility and minimise the energy cost for the benefit of consumers. [16] builds a game-theoretic model between utility and consumer, by minimising the energy cost for both parties, finds out the optimum scheduling for consumers.

In this thesis project, energy consumption scheduling is built for household consumers to minimise their energy costs. To build an optimum scheduling, a game theoretical model for only consumers is suggested.

2.4 Micro-Generation

The term 'micro-generation' is used to refer to electricity generation systems of the smallest capacity, which covers generation of electricity up to 50 kWe [62]. Domestic-scale micro-generation embraces a range of technologies that are presently at varying stages of development and commercial availability. These include small-scale photovoltaic (PV) arrays, micro-hydro generation, micro wind generators and micro Combined Heat and Power (μCHP) systems.

2.4.1 Small-scale Photovoltaic (PV) Arrays

Photovoltaic (PV) systems produce electricity from sunlight. Small-scale PV systems are applied in the residential area in connection to the central grid or as autonomous units with an electricity production capacity between 1 to 10 kWe.

Four types of technologies are in use in the Netherlands: Mono-crystalline silicone (sc-Si), Multi-crystalline silicone (mc-Si) which are crystalline silicone based cells and Amorphous-silicon (a-Si), Copper-indium-diselenide (CIS/CIGS) which are thin-film solar cells [2]. On this moment, approximately 10% of the total installed capacity of PV panels in the Netherlands exists of thin-film solar cells, and 90% of crystalline silicon based cells. Due to lower production cost (lower material use), the market rate of thin film solar cells shows an increase and this trend is likely to continue in the future [42].

The presence of a solar power system plays an increasingly important role in terms of the sustainability. In The Netherlands energy efficiency of houses is measured by a method called energy performance coefficient (energieprestatiecoëfficiënt, EPC). In 2006, The Netherlands introduced a regulation for new homes to comply with the minimum of 0.8 Energy Performance Coefficient (EPC). On 1 January 2008 the Dutch government introduced a new regulation including the sale of existing homes will be based on a label that indicates how well the house performs on energy field. In these regulations, the presence of a solar power-system in houses is taken positively into account for the energy efficiency of the houses. All these regulations motivate investors to build solar power-system to their new houses, which increases the value of their real estate [2].

3 Electricity Demand Profiles

In electricity cost calculations, electricity consumption and electricity price of household consumers are multiplied with each other. In Chapter 4, time-variable electricity pricing model will be suggested for household consumers, in this case electricity demand of "shiftable" and "non-shiftable" loads is needed for every hour, so then these load profiles can be used as an input to calculate the electricity costs of household consumers. Electricity demand profile of a household shows electricity usage of a household in every given time interval of a day. Time interval can be 1-minute to 1-hour.

Measured data on electricity demand profiles is hard to find. In the Netherlands, utility companies keep their data confidential for commercial and data privacy reasons, and have not always been able to retrieve it when needed. Because it is difficult to find measured data on electricity demand profiles, electricity demand profiles can be generated through modelling. The two general categories of energy demand profile model are known as "top-down" and "bottom-up" approaches.

Top-Down Models

In the top-down case, the models are concerned with breaking-down an overall view of the whole system and are usually based upon aggregated consumption data. Top-down models determine the effect on energy consumption due to on going long-term changes or transitions within the residential sector, primarily for the purpose of determining supply requirements. Variables, which are commonly used by top-down models include macroeconomic indicators such as gross domestic product (GDP), employment rates, and price indices; climatic conditions, housing construction/demolition rates, and estimates of appliance ownership and number of units in the residential sector.

Figure 3.1 shows two groups of top-down models: econometric and technological. Econometric models are based primarily on price (of, for example, energy and appliances) and income. Technological models attribute the energy consumption to broad characteristics of the entire housing stock such as appliance ownership trends. In addition there are models, which utilize techniques from both groups.

Top-down models operate on an equilibrium framework, which balances the historical energy consumption with that estimated based on input variables. For example, if housing construction increased the number of units by 2%, an increase in total residential energy consumption of 1.5% might be estimated by the top-down model, as new houses are likely more energy efficient. If this construction was increased to 10% of the units the top-down model could have difficulty in producing an appropriate estimate, as the vintage distribution of the housing stock would have changed significantly.

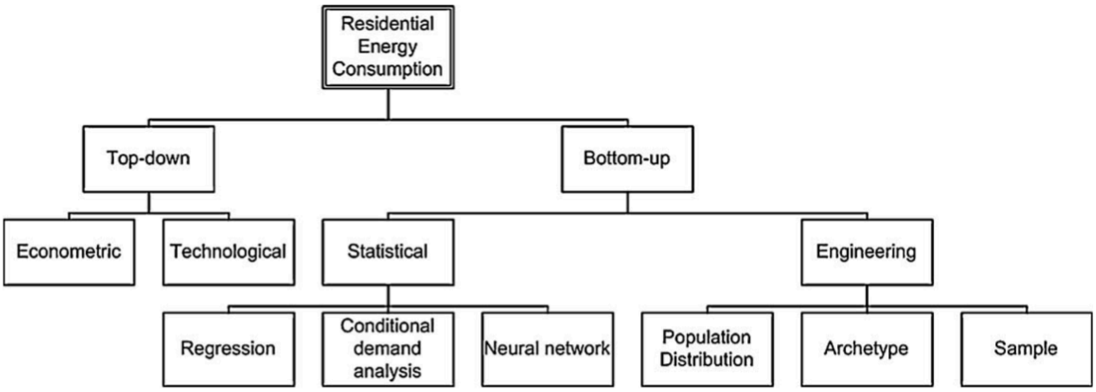


Figure 3.1 Top-down and bottom-up modelling techniques for estimating the regional or national residential energy consumption (Swan & Ugursal, 2009)

Bottom-Up Models

The bottom-up approach encompasses all models, which use input data from a hierarchal level less than that of the sector as a whole. Models can account for the energy consumption of individual end-uses, individual houses, or groups of houses and are then extrapolated to represent the region or nation based on the representative weight of the modelled sample. The variety of data inputs results in the groups and sub-groups of the bottom-up approach as shown in Figure 3.1 [76].

Statistical methods (SM) rely on historical information and types of regression analysis, which are used to attribute dwelling energy consumption to particular end-uses. Once the relationships between end-uses and energy consumption have been established, the model can be used to estimate the energy consumption of dwellings representative of the residential stock. Engineering methods (EM) explicitly account for the energy consumption of end-uses based on power ratings and use of equipment and systems and/or heat transfer and thermodynamic relationships.

Common input data to bottom-up models include household properties such as geometry, envelope fabric, equipment and appliances, climate properties, as well as indoor temperatures, occupancy schedules and equipment use. This high level of detail is the strength of bottom-up modelling and gives it the ability to model technological options. Bottom-up models have the capability of determining the energy consumption of each end-use and in doing so can identify areas for improvement. As energy consumption is calculated, the bottom-up approach has the capability of determining the total energy consumption of the residential sector without relying on historical data. The primary drawback caused by this level of detail is that the input data requirement is greater than that of top-down models and the calculation or simulation techniques of the bottom-up models can be complex. Bottom-up modelling will be most appropriate to meet the modelling requirements of individual households.

	Top-down	Botom up statistical	Bottom up engineering
Positive attributes	Long term forecasting in the absence of any discontinuity	Encompasses occupant behaviour	Model new technologies
	Inclusion of macroeconomic and socioeconomic effects	Determination of typical end-use energy contribution	"Ground-up" energy estimation
	Simple input information	Inclusion of macroeconomic and socioeconomic effects	Determination of each end-use energy consumption by type, rating, etc.
	Encompasses trends	Uses billing data and simple survey information	Determination of end-use qualities based on simulation
Negative attributes	Reliance on historical consumption information	Multicollinearity	Assumption of occupant behaviour and unspecified end-uses
	No explicit representation of end-uses	Reliance on historical consumption information	Detailed input information
	Coarse analysis	Large survey sample to exploit variety	Computationally intensive
			No economic factors

Table 3.1 Positive and negative attributes of the three major residential energy modeling approaches. (Swan & Ugursal, 2009)

In this thesis, a bottom-up statistical approach is followed.

3.1 Electricity Demand Profile Model

Loughborough University has built a 1-minute resolution household occupancy model, using a Markov-chain technique where the activity state in each household at each time step depends on the previous one, together with the probability of that state changing. This starts with inputs for house size, occupancy and number of appliances owned; a simulation is carried out for the number of persons in the house and active at any time, using UK national time-use survey data.

Then, the same time-use survey is used to predict the probability that the occupants in the house will change their activity, depending on what they happen to be doing at any one time. This in turn drives which electrical appliances are on and build a 1-minute resolution household demand profile model. The load profiles for individual appliances are taken from measured data where possible. The electricity consumption profile generated by the model was calibrated against 1-minute overall electricity use measurements from 22 houses.

At the averaged level, the model output showed the same mean and other statistical properties as the measured data. However, it was less good at simulating individual houses, and in particular did not fully represent the variation between highest and lowest demand households. No input level data was collected on activities to allow comparison of simulated and actual usage at appliance level.

In this thesis, demand profile of the example household will be generated using Loughborough University's model due to the time constraints. This model has been modified using the Dutch household appliance usage statistics, which differs from UK household usage statistics. Moreover UK time of use statistics was used to build occupancy pattern model assumed to be the same for the Netherlands. Even though these changes have been applied, the new model has not been validated by comparing to the real demand profile in The Netherlands due to the lack of real data.

The structure of the model is presented in Figure 3.2. On the left of the diagram, there are set of daily activity profiles, which represent the likelihood of people performing different activities at different times of the day; these profiles are the same for all households. To the right of the diagram, the outer square block represents the example household. Example household is assigned an active occupancy data series for three-person house and a set of installed appliances. Each appliance is mapped to one of the daily activity profiles. When an appliance switch-on occurs, the appliance power use characteristics are used to determine its electricity demand (including the reactive power demand). Adding the power demands of all appliances within the example household gives the household demand.

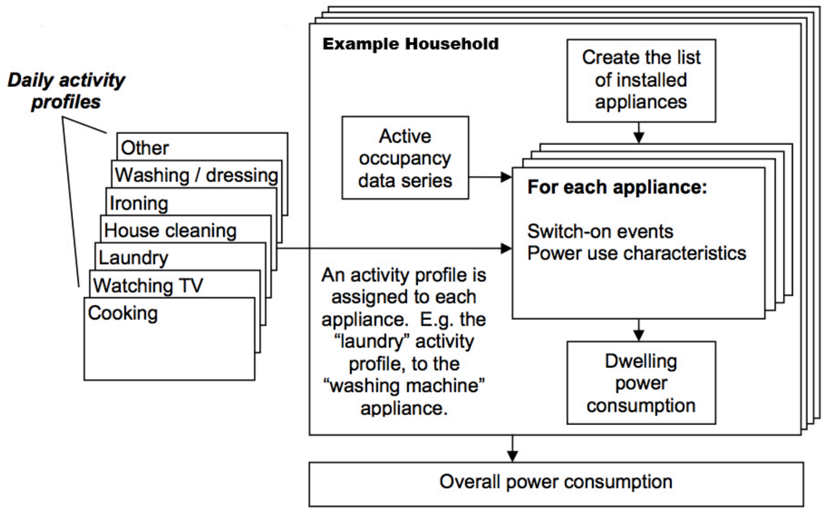


Figure 3.2 Electricity demand model architecture [66]

3.2 Occupancy Pattern Model

The different households have different life styles. The total load profile shape will of course vary from day to day and house to house. The factors influencing the occupancy pattern are as follows:

(1) The number of occupants
(2) The time of the first person getting up in the morning and the last person going to sleep
(3) The period of the house unoccupied during the day.

It is important to identify the cluster of households when analyse the load profile, because the load profile depends very much on the occupancy pattern. In the case of lack of information about household occupancy pattern, it is proposed five most common scenarios of household occupancy pattern by [89], same scenarios can be applied in the Netherlands.

Scenarios	Type	Unoccupied Period
1	Part-time working morning session 1/2	09:00-13:00
2	Full-time working	09:00-18:00
3	Part-time working 2/3	09:00-16:00
4	No working	N/A
5	Part-time working afternoon session 1/2	13:00-18:00

Table 3.2 Occupancy pattern for a three-person household offered by [89]

In this thesis, occupancy modelling approach of [65] is followed. In [65], a large survey of how people use their time was conducted in the United Kingdom in year 2000, known as the Time Use Survey (TUS), is used to model occupancy. Time of Use Survey contains detailed 24-hour diaries, completed at ten-minute resolution by many thousands of participants. The data includes the location of the participants, at each ten-minute diary period, and can thus be used to identify the number of active occupants in a house.

An example of the nature of active occupancy profiles are taken from TUS is shown in Figure, where fifty people are individually represented. The black horizontal bar shown for each person represents the times of the day when they are active within their dwelling. The active occupancy during the hours from 00:00 to 07:00) can be seen to be sparse, as would be expected. It can be seen that activity increases during the day, and reaches a maximum during the evening.

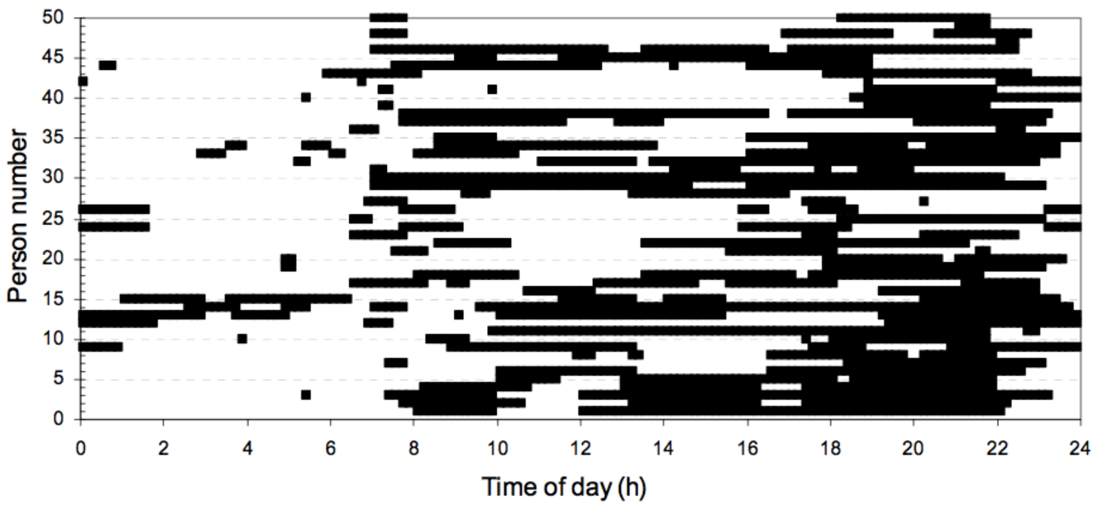


Figure 3.3 Fifty example active occupancy profiles drawn from the TUS data [65]

The TUS data also provides sufficient detail to determine which occupants live together. People's activity within the same household is often correlated and this is evident in the TUS data.

[65] presents their model, which provides a stochastic simulation of active occupancy patterns in UK households. The model uses a Markov-Chain technique to generate further data with statistical characteristics that match the original. An implementation of the model, in the form of a Microsoft Excel workbook, is available for free download and this workbook is adopted to statistics of The Netherlands and adapted for specific application [48].

The technique of building transaction probability matrices from the source data and using these to generate synthetic data series is very effective and computationally efficient. The statistical characteristics of the original TUS data and simulation output correlate very closely.

3.3 Appliance Activity Model

In addition to the level of active occupancy within dwellings, a second concept is required in order to represent the use of different types of appliance at different times of the day, depending upon what activities the occupants are likely to be engaged in. Each daily activity profile, on the left of Figure 3.2, quantifies the probability of the specified activity being undertaken as a function of time-of-day. The set of profiles includes variants to take account of the current number of active occupants, in case of the example household 3-person and whether it is a weekday or a weekend day.

For example, people will commonly use cooking appliances, such as ovens and hobs, around the meal times of the day, whilst television usage mainly occurs in the evening. This concept is represented using "activity profiles" which, like the active occupancy data, are also derived from the TUS data set.

The activity profiles are linked to the use of individual appliances. As an example, the activity of watching television will require a television appliance to be in use. Similarly, a laundry activity may well require a washing machine to be used. By assigning an activity profile to each appliance, the likelihood of that appliance being used at different times of the day may be represented.

3.3.1 Appliances

Proposed model of [66] uses the appliance it refers to any individual domestic electricity load, such as a television, washing machine or vacuum cleaner. It is therefore a 'bottom-up' model, in common with those developed by [58], [15], [89] and [6].

An important feature of model in [66] is in its approach to representing time-correlated appliance use. The appliances in this model are configured using statistics describing appliance annual energy use and appliance power characteristics, including steady-state consumption or typical use cycles as appropriate. The next stage of model development considers when the specific appliances are likely to be used.

Installed Domestic Appliances

Domestic appliances can be classed as:

1) Cooking appliances: Most of the energy used in cooking goes to the hob and oven. Since electric hob is not a popular consumer appliance, electric oven and microwave oven are used in the simulation.
2) Cold appliances: Households will have one or more cold appliances, which are on all the time. These consume electricity in a cyclical pattern over 40 minutes - 1 hour, at a more or less constant rate unless they are unsuitable location or are being left open regularly when in use.
3) Consumer electronics: Televisions and appliances associated with them such as speakers, set top boxes, games consoles and DVD players is the highest growth area of household energy. Many households have multiple groups of these, in use simultaneously as different family members pursue their own activities in different rooms. In the simulation, only two televisions and a DVD player is selected for the simplicity of calculations. Energy use depends partly on how many appliances there are and their power rating, but also very much on how they are used – whether they are the main form of entertainment, as a constant background to other activities, whether they are switched off or on standby when not in use.
4) Wet appliances: Dishwashers, washing machines and tumble driers are heavy electricity consumers – they draw high peak power, and have long cycle times. Their energy consumption per cycle varies depending on the cycle length and temperature setting, and also on whether they take in hot as well as cold water. However their total contribution to household energy depends on household size, attitudes and practices. For example, some households who have dishwashers may choose to use them all the time whether they are full or not, others will prefer to wash small loads by hand and only deploy the machine when there is a large party.
5) Miscellaneous: The extent to which computers and other miscellaneous devices contribute to a household's energy use is not possible to predict in advance. If someone in the house is regularly working from home, then the computer and associated peripherals may be significant. The other electricity appliances are kettle, iron, and vacuum cleaner, etc. The usage pattern of this kind of appliances also depends on the household occupancy pattern and lifestyle.
6) Lighting: Lighting is complicated to measure because although the total energy used is high, this is the product of multiple small power light bulbs. Lighting use varies during the year depending on the number of daylight hours, as well as on occupancy patterns. However, attitudes also have a large influence on whether or not low energy fittings are used, on how many lights are switched on at any time, and whether or not lights are routinely switched off when occupants move from room to room.

Common appliances are selected for the simulation of example household. These appliances are refrigerator, freezer, cd player, alarm clock, hi-fi, iron, vacuum cleaner, personal computer, one TV, DVD, TV receiver box, oven, microwave, dishwasher, washing machine, tumble dryer.

Appliance annual energy use

Each appliance is assigned an annual demand in kWh/y. This data is based on the 'basisonderzoek elektriciteitsverbruik kleinverbruikers', which is a detailed research on retail electricity in the Netherlands. This data is taken from different sources, where the findings are published, [71], [72] and [44]. The data is given in the Table 3.3, the data with star is taken from [66].

Category	Selected Appliances	Energy used (kWh/year)	Ownership level (%)
Entertainment Appliances	TV	207	98
	TV receiver box	131	93.4*
	VCR/DVD recorder	108	48
	Computer	135	74
	Printer	49*	66.5*
	CD player	24	91
	HiFi	89*	90*
Wet Appliances	Washing Machine	230	96
	Dishwasher	220	47
	Drier	599	59
	Refrigerator	225	100
	Freezer	380	79
Cooking Appliances	Electric oven	55	61.6*
	Microwave oven	35	84
	Kettle	161*	97.5*
Miscellaneous	Iron	20	90*
	Vacuum cleaner	54	93.7*
	Alarm clock	18*	90*

Table 3.3 Selected Appliances and their energy usage per year and ownership levels in The Netherlands [71], [72], [44].

Appliance power characteristics

Appliance power characteristics are used from [66]. Each appliance in the model has two states: it may be either on or off. The off state includes the representation of standby, in that an appliance may be configured to use power even when off.

Many appliances are assumed to have a constant power demand when switched-on. However, in pursuit of a one-minute time resolution for the final model output, some appliances are represented by time-varying demands.

Finally, each appliance is assigned an appropriate power factor, representing a mean value over a one-minute interval. These power factors are used from [66].

A unity value is used for resistive heating appliances, such as an oven or iron. Electronic entertainment appliances are configured with a value of 0.9. Cooling and washing type appliances are configured with a value of 0.8. These figures are based on measurements made with a plug-in power meter on a small number of appliances.

3.3.2 Appliance-activity mapping

Appliances of which use is dependent upon a particular activity-taking place are assigned to their relevant activity profile. There may be multiple appliances assigned to a single activity. For example, the electric hob, oven, microwave, small cooking appliance and dishwasher are all assigned to the cooking activity. This does not imply that all these appliances are necessarily used whenever cooking takes place; it simply models the possibility of their being used and possibly simultaneously.

Appliances not associated with any particular activity are assigned to the 'other' activity profile, which covers two specific cases:

- For some appliance types, there are no activity profile categories that describe when the appliance is likely to be used. A telephone is an example. In this case, the appliance use is taken to be dependent only upon active occupancy within a dwelling.
- Some appliances do not depend on active occupancy at all. In this model, the cycling of cooling appliances such as a fridge or freezer, do not depend on people being active within a dwelling.

3.3.3 Switch-on events

The procedure to determine whether an appliance switch-on event occurs at each time step of a simulation is presented in Figure 3.4. The following steps occur:

- Firstly, the activity profile is selected according to the appliance activity, the current number of active occupants and whether it is a weekend or not.
- Secondly, the probability that any of the active occupants are engaged in the activity at this time is read from the activity profile.
- Thirdly, the activity probability is multiplied by the calibration scalar. A discussion of how the calibration scalar is derived is presented later.
- Finally, the result of the previous step is compared to a random number between zero and one. If the probability is more than the random number, then a switch-on event occurs.

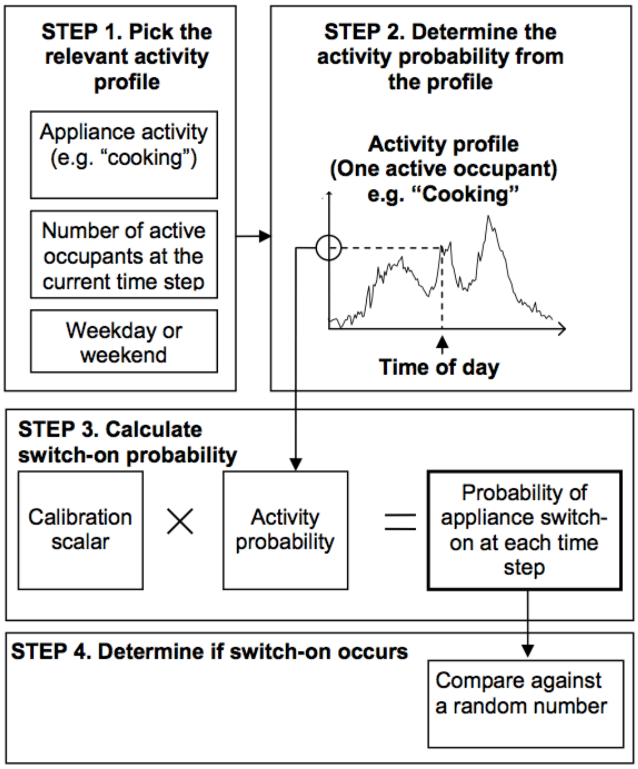


Figure 3.4 Switch-on events [66]

3.3.4 Appliance calibration scalars

Each appliance has a "calibration scalar" which is factored into the probability of switch-on as shown in Figure 3.4, and thus determines the average number of times that the appliance is used in a year. In the case of automatic appliances such as fridges, this corresponds to the number of times that the thermostat starts the compressor. A calibration scalar is adjusted so that, over a very large number of stochastic simulation runs, the mean annual consumption of the appliance will be correct.

For example, the chest freezer in the model uses 271 kWh/y. It draws 190 W for 14 minutes on each operating cycle and uses no power on standby. It must therefore cycle 6116 times per year. Additionally, each 14-minute run is followed by a delay of 56 minutes during which the appliance may not start again; this represents the effect of the thermostat dead band. This leaves approximately 95000 minutes of the year when a start event can occur. Thus the mean time between start events, excluding the time when the appliance is in a cycle, is 95000/6116= 16 minutes. Since the freezer appliance is not dependent on active occupancy, its activity probability is taken as unity, and thus, referring to Figure 3.4, the calibration scalar is simply 1/16 min-1.

A similar calculation can be performed for appliances that do depend on daily activity profiles, but it is more complex. This is because it is necessary to take into account the statistical distributions of both the occupancy and the activity profiles.

The overall mean value of an activity-taking place at a time step must first be calculated. This may be achieved by using Bayes' conditional probability theorem. The first input to this is the probability of each level of active occupancy (none, one, two, three, four or five) at each time step of the day. This may be determined from the occupancy model. The second input is the conditional probability of an activity-taking place, given each level of active occupancy. This information is available from the activity profile.

This mean probability of an activity-taking place, when multiplied by the calibration scalar, should equal the mean probability of an appliance switch-on event. The former value is determined by the same method as described above, such that the required number of cycles per year occur as required to give the correct overall energy use. Of course, appliances that do depend on daily activity profiles may only start if there is active occupancy within the household.

3.4 Lighting model

A key motivation for the use of domestic lighting is the occupant's perception of the natural light level. Clearly, people will use lighting after dusk or before dawn, or when weather conditions, such as overcast skies, reduce the available light. The majority of domestic lighting use is the result of people switching on lights as they move around the dwelling. The concept of active occupancy is therefore useful in determining when people are within a dwelling and be available to use lighting as is required. The model of active occupancy, described in the previous chapter, is used to provide simulations in this context. It is common for multiple occupants to share the use of lighting, for example, when two or more people are within the same room. Using the number of active occupants as an input enables this sharing to be represented. The term "lighting unit" is used to describe one or more bulbs that are operated by a single switch. As an example, this could be a single bulb in a hallway, or it could represent a set of halogen down lights within a kitchen. It is important to appropriately represent the numbers and types of bulbs within each dwelling that is to be simulated. In reality, the lighting configuration within each dwelling will vary as a result of choices made by the occupants. Statistics from Domestic Lighting 2008 Report of The Lighting Association in Telford, UK are used to randomly populate each dwelling with an appropriately representative set of lighting units. The relative usage of different lighting units varies around the dwelling. For example, lighting units in living areas, such as kitchens, will be used more than loft or cellar areas. The model represents this variation of use with a weighting factor, picked at random from a probability distribution.

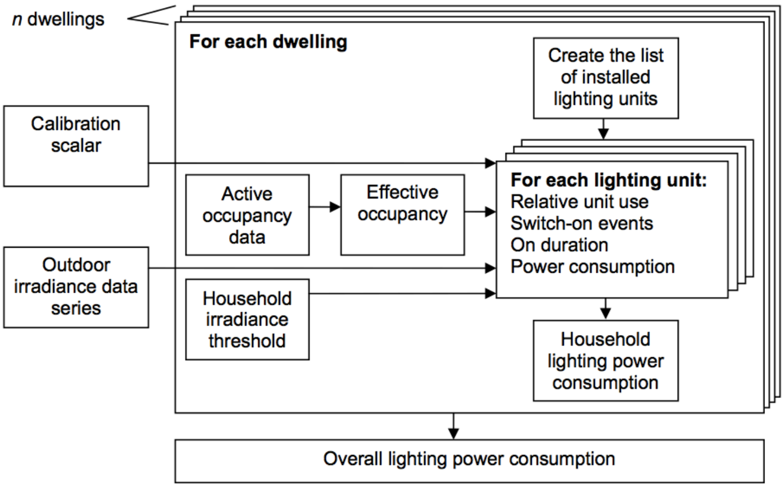


Figure 3.5 Whole-dwelling lighting demand model architecture [67]

The outdoor irradiance data series has global scope, such that all dwellings in the simulation are subject to the same level of natural light. A second global variable is the calibration scalar: this is used to calibrate the model, such that the overall mean electricity demand of the lighting over a large number of simulations, will meet a required level, such as that from national statistical data. The main block of the diagram represents the inputs, outputs and processing performed for each dwelling in a simulation.

Each dwelling is assigned an active occupancy profile from the output of the model described in Section 3.2. The level of active occupancy is transformed into an "effective occupancy" value, in order to take sharing into account. Each dwelling is also assigned a set of lighting units: the number and power ratings of all lights are thereby determined.

Furthermore, each dwelling is assigned an irradiance threshold that defines the natural light level below which occupants will consider that lighting is required. The inner block, shown in the Figure 5, represents the processing that occurs for each lighting unit at each time step of a simulation. The combination of the effective occupancy, the irradiance level, the relative usage and the calibration scalar, is used to stochastically determine if a switch-on event occurs at each time step. When this does occur, the length of time that the unit remains on is determined stochastically, by picking a value at random from an appropriate distribution. Finally, at each time step, the power demand of each lighting unit that is switched on is summed at each time step to provide the overall demand.

3.5 Electricity Demand Simulation

In Figure 3.6, it is shown an example of April weekday occupancy simulation of a 3-person house.

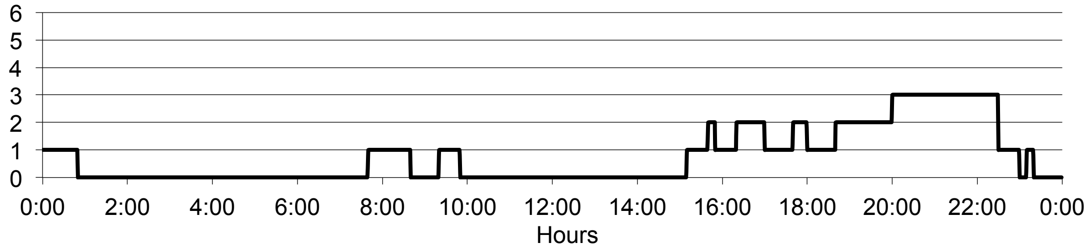


Figure 3.6 Household active occupancy profile

In this simulation, the household has been allocated as having three total residents, but in this run, three occupants are only active between 20:00 to 22:30. The profile is typical in that there is no active occupancy between 01:00 to 07:30 and the level varies throughout the day.

The list of appliances that has been allocated to the household is listed in Table 3.3. The simulated use of these appliances throughout the day is shown on the figures below.

Cold appliances such as refrigerator and freezer are seen to cycle at intervals throughout the whole day regardless of active occupancy. The usage of these appliances is not shiftable.

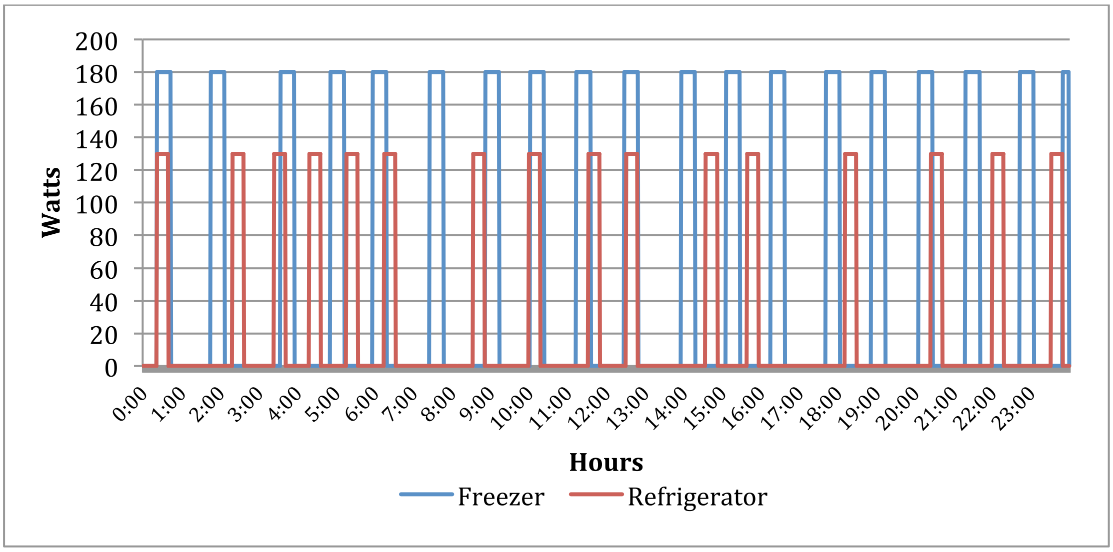


Figure 3.7 Consumption pattern of cold appliances

Usage of kitchen appliances is shown in the Figure 3.7. Electric oven and kettle are used in the morning, probably warming up some bread and boiling water for tea. Microwave oven is used in the evening when two active occupants were home, probably for a dinner and kettle usage in the evening is for some hot beverages after dinner. Cooking appliances are dependent on active occupancy and time of use survey; the consumption cannot be shifted since consumers demand the usage of these appliances for their convenience.

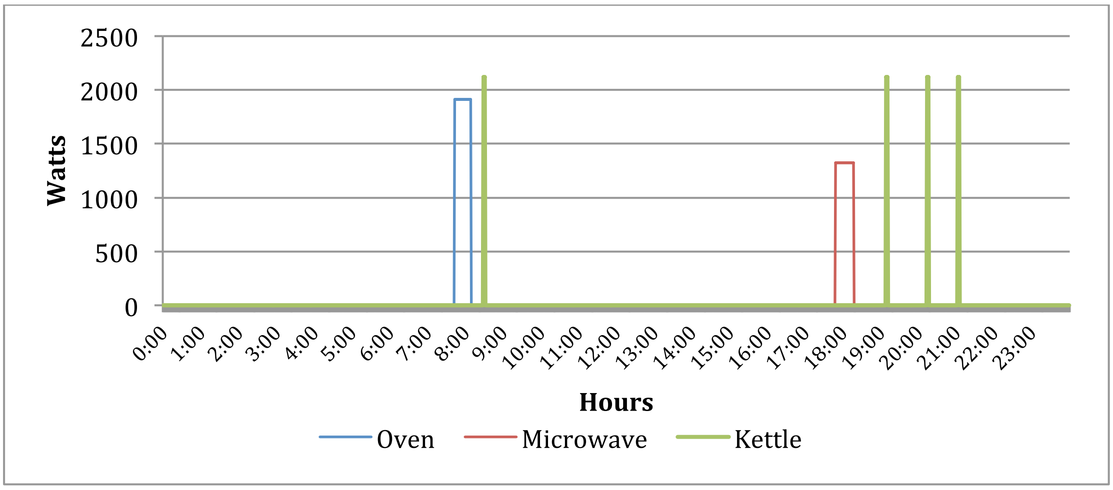


Figure 3.8 Consumption pattern of cooking appliances

Usage of entertainment appliances is also active occupancy and time of use survey dependent. PC is used when the house is occupied with more than two consumers, TV and TV receiver are correlated turned on at same time. For this simulation, household did not use their DVD and CD player for the given day.

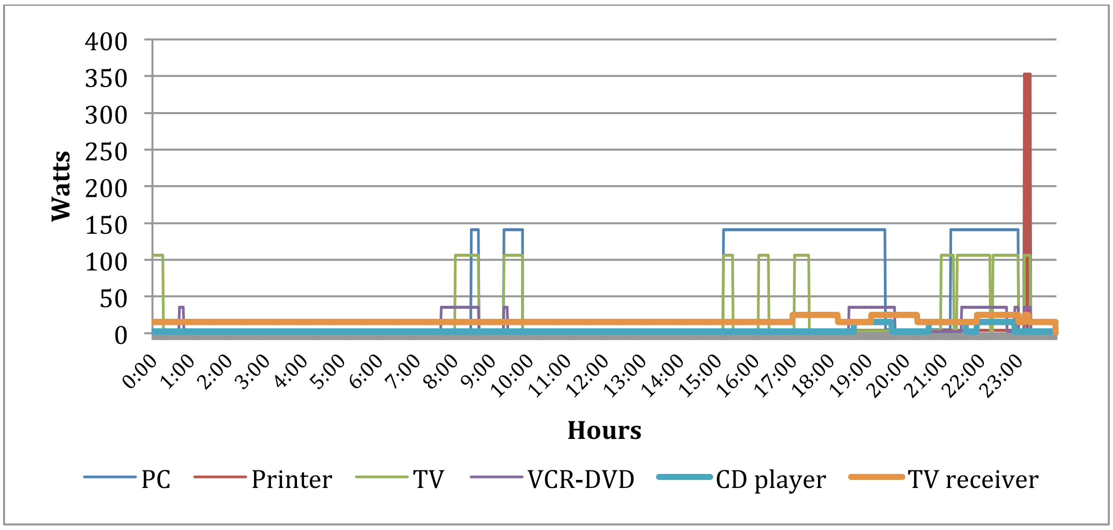


Figure 3.9 Consumption pattern of entertainment appliances

Wet appliances are also dependent on consumer convenience, but consumers would like to shift the time to wash their clothes for couple hours, while they would not like to shift the time to drink a cup of tea or watch TV for couple hours. Demand for wet appliances can be shifted to different times and this characteristic for these high energy requiring appliances are important for consumers. In the figure, only the dishwasher and washing machine are used for the given day.

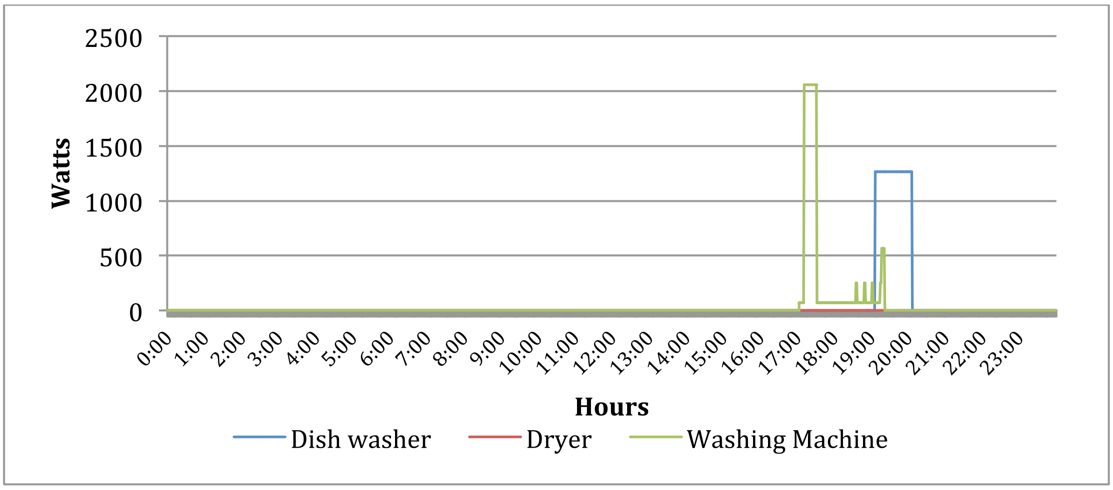


Figure 3.10 Consumption pattern of wet appliances

In Figure 3.11, it is shown electricity consumption profile of the example 3-person household of which active occupancy simulation given below.

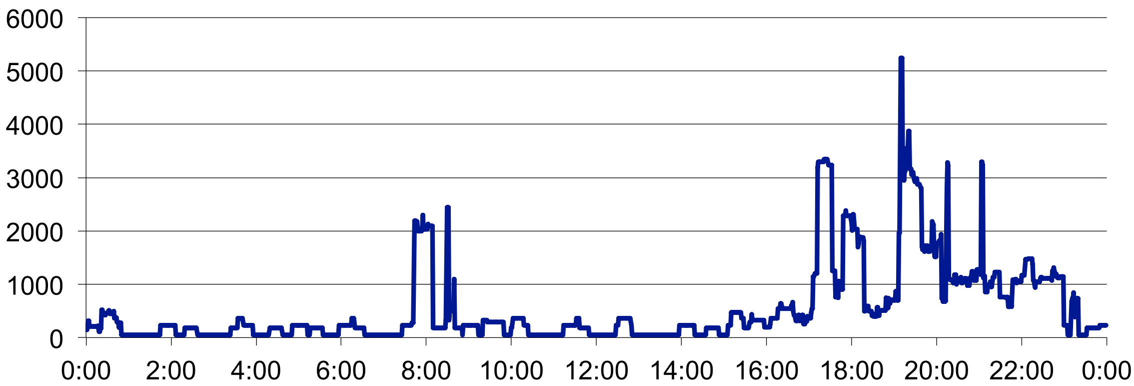


Figure 3.11 Simulation output; aggregated total

4 Electricity Pricing

Electricity production is dependent on the demand; if production is more than the demand, then because electricity is not economically storable, production will be wasted. That is why electricity production is subject to rigid short-term capacity constraints. Since demand is highly variable, there will be times when there is plenty of capacity, and the only marginal costs of producing electricity will be fuel and operation and maintenance (O&M) costs; at the other times, the capacity constraint will be binding, causing the marginal cost to increase greatly, and wholesale market prices to rise. The result of this structure is that the wholesale price of electricity, reflecting the supply/demand interaction, varies constantly. In most markets, the wholesale price changes every half-hour or hour.

The end-user customer however sees the retail price, which typically is constant for months at a time. Retail price does not reflect the hour-by-hour variation in the underlying wholesale cost of electricity [10]. In The Netherlands, residential electricity consumers pay retail electricity prices, which is some kind of average price. Electricity trading companies usually offer small consumers the choice between a floating price which changes monthly and is calculated as a weighted average of the spot price, and a fixed price that is constant for a longer period of time, usually 1, 2, 3 or 5 years. In either way the consumer faces the same price for all hours of the day.

A number of programs have been implemented or proposed to make the economic incentives of customers more accurately reflect the time-varying wholesale cost of electricity. Opponents have expressed concern that these programs expose customers to too much price volatility [10]. In this thesis, the general wholesale electricity market scenario is considered as in Figure 4.1, where each retailer/utility serves a number of end users. The time-varying price information, reflecting the wholesale prices, is sent to the users by the retailer over a digital communication infrastructure, a local area network (LAN).

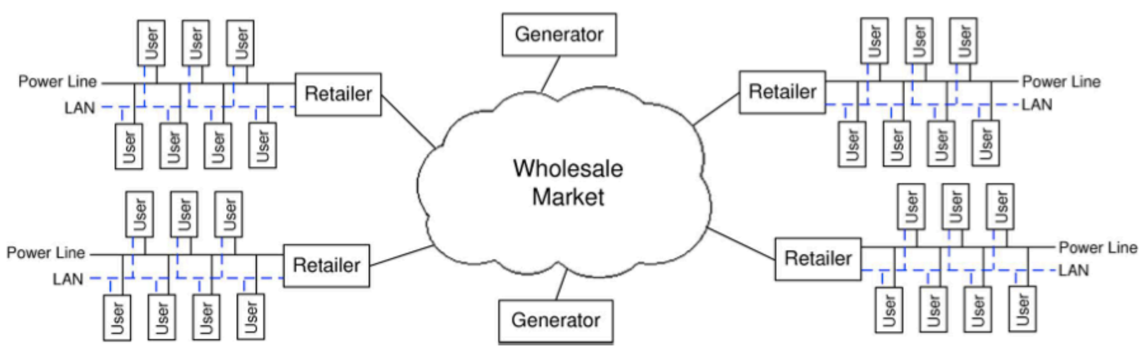


Figure 4.1 A simplified illustration of the wholesale electricity market formed by multiple generators and several regional retail companies [51]

4.1 Pricing Schemes

The supply/demand of electricity balance changes continuously and there can be a great deal of uncertainty about supply and demand in advance of any given period. This raises the two fundamental issues in designing time-varying retail electricity prices:

Granularity of prices: The frequency with which retail prices change within the day or week. The single retail price does not have granularity. Real-time prices change every minute and are announced only at the minute in which they are applied.

Timeliness of prices: The time lag between when a price is set and when it is actually effective. The single retail price is set months before some of the hours which it is applied. When timeliness is discussed as part of RTP, the issue is whether prices should be set a day ahead or an hour (or less) ahead.

In case of fixed pricing, there is not granularity, nor timeliness of prices. Programs that have been designed for implementing time-varying retail prices, range, accordingly different price granularity and price timeliness levels, from slight augmentations on flat pricing to more radical change that would make retail electricity markets more closely resemble the wholesale electricity markets.

4.1.1 Fixed pricing

Retail price does not reflect the hour-by-hour variation in the underlying wholesale cost of electricity [10]. In The Netherlands, residential electricity consumers pay retail electricity prices, which is some kind of average price. Electricity trading companies usually offer small consumers the choice between a floating price which changes monthly and is calculated as a weighted average of the spot price, and a fixed price that is constant for a longer period of time, usually 1, 2, 3 or 5 years. In either way the consumer faces the same price for all hours of the day.

4.1.2 Real time pricing (RTP)

Real-time prices are typically set either “day-ahead” or “real-time.” In the day-ahead formulation, the retail provider announces all 24 hourly prices for a given day at one time on the prior day. In the real-time approach, the retail provider announces prices on a rolling basis, typically with the price for each hour determined between 15 and 90 minutes prior to the beginning of that hour. In terms of economic incentives and efficiency, RTP using real-time announced prices offers the greatest value [10], this has been shown in Section 4.2.

RTP programs currently in effect typically announce the prices for all hours of a day on the previous day. Obviously, a longer lag time between the price announcement and the price implementation will result in prices that less accurately reflect the actual real-time supply/demand situation in the market. That is the reason why wholesale electricity prices must be forecasted with high precision, taking into account of probable “re-bound” effects by the retail consumers.

In The Netherlands, there are not examples of time-varying prices in retail electricity market. There are several examples in USA, e.g: Ameren Illinois[1], PGE (Pacific Gas and Electricity Company)[2]

4.1.3 Time of Use Pricing (TOU)

Under TOU, the retail price varies in a pre-set way within certain blocks of time. The rates for each time block (usually called peak, shoulder, and off-peak) are adjusted infrequently, only two or three times per year in most cases. Price is the same at a given time of day (on a weekday) throughout the month or season for which the prices are set. TOU retail pricing lacks both the granularity and the timeliness of RTP.

The lack of timeliness of TOU prices means that they cannot capture any of the shorter-term variation in supply/demand balance. In addition, TOU programs don't reflect expected wholesale market variation very well, due to the lack of price granularity.

4.1.4 Critical Peak Pricing Programs (CCP)

CPP has some attributes of RTP and some of interruptible programs. CPP programs usually start with a TOU rate structure, but then they add one more rate that applies to "critical" peak hours, which the utility can call on short notice. While the TOU program has poor granularity and timeliness, as discussed above, CPP allows a very high price to be called on very short notice, thereby improving both aspects of the rate structure. Thus, CPP is similar to interruptible programs except prices are not set so high as to cause most customers to reduce consumption to zero.

CPP programs typically limit the utility to call number of critical peak hours per year. CPP is a clear improvement on TOU with demand charges, because the additional charges are based on consumption when the system is actually constrained, rather than when the particular customer's demand peaks. CPP has some of the advantages of RTP, because retail prices are allowed to vary with the wholesale market. Of course, CPP is much more constrained than RTP: the CPP peak price is set in advance and the number of hours in which it can apply is limited.

4.2 Comparison of Time-Varying Prices to Single Price

It is assumed that the electricity market behaves in competition. In competitive markets, firms are free to set price and quantity; if a firm sets a price above the prevailing market price, its product will not be purchased; if it sets its price below the market price, its profits will be needlessly lost, since it can get as many customers as it wants by pricing at the market price [82].

It is assumed that there are only two levels of demand: peak and off-peak. These

[1] Ameren Illinois Company Real Time Pricing Website: https://www2.ameren.com/RetailEnergy/realtimeprices.aspx

[2] PGE Company Real Time Pricing website: http://www.pge.com/tariffs/energy_use_prices.shtml

levels are drawn in blue colour and denoted as D_{peak} and $D_{off-peak}$ on the Figure 4.2. It is also assumed that all producers have the same cost of production, which is the marginal cost, MC . Different prices are charged during peak and off-peak times, denoted as P_{peak} , P_{op} . Q_{peak} and Q_{op} denotes the power during peak-demand and off-peak demand times.

Total installed capacity K equals the peak-demand power Q_{peak} ; if total installed capacity is more than the peak-demand power $K > Q_{peak}$, then there will be waste of production; if total installed capacity is less than the peak-demand power $K < Q_{peak}$, then there will be blackout. Market supply curve is flat at MC out to K and then vertical, as drawn in green colour on the Figure 4.2.

During off-peak power demand, if producers try to charge a price above P_{op} , it will be unable to sell its power according to competitive market definition. During peak-demand power, no producer will sell below the price P_{peak} , because any producer can sell all of its output at that price. If any producer tries to charge more than P_{peak} , it will find that its unit sales decline according to competitive market definition.

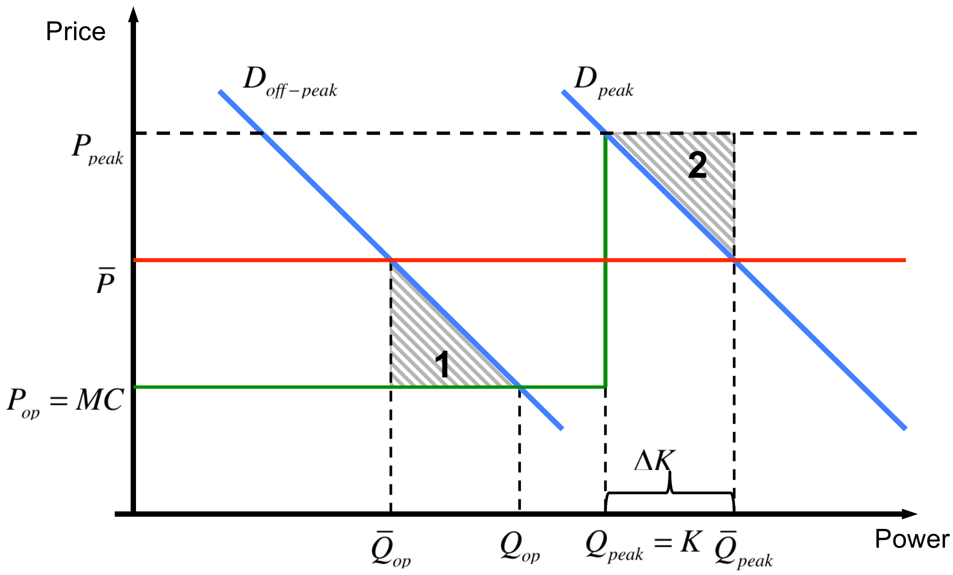


Figure 4.2 Varying pricing and single pricing shown [10]

The firms charge the same price for both peak and off-peak demand. If the firms are still to break even overall, the price will lie between the peak and off-peak price. This single price is denoted as $\bar{P}$ and it is shown in red colour in the Figure 4.2.

There are two deadweight loss areas, shaded and numbered on the Figure 4.2. Deadweight loss occurs when there is a loss of economic efficiency. In other words; the total loss of producer and consumer surplus from underproduction and from overproduction is referred to as a deadweight loss [43].

During the off-peak demand, single-price restriction result increase in the price due to $\bar{P} > MC$ and inefficiently discourage off-peak consumption. Off-peak demand power will decrease as is shown in the Figure 4.2, new off-peak power demand $\bar{Q}_{op}$. These changes in price and quantity are shaded as deadweight area 1 in the Figure 4.2.

During the peak demand, single-price restriction results in a price $\bar{P}$ for peak demand that is below P_{peak} . This will increase the peak-demand power from Q_{peak} to $\bar{Q}_{peak}$. The total installed capacity is built to answer the peak-demand in power, $Q_{peak} = K$, but now the new peak-demand is higher than the total installed capacity, $\bar{Q}_{peak} > K$. Theoretically this situation should cause shortage, but in reality capacity is expanded to meet the excess demand. This excess demand has to be supplied by the producers, when they make loss from each unit, $P_{peak} - \bar{P}$. This inefficiency is shaded as deadweight area 2 in the Figure 4.2. With time-varying pricing of electricity, this excess capacity is not necessary because higher prices at peak times encourage customers either to shift peak consumption to off-peak or to reduce consumption at peak times.

So far analysis has considered only the case of a competitive electricity market, the benefit of instituting time-varying prices is greater in non-competitive electricity market. Producers are able to exercise market power by raising price above the competitive level in non-competitive markets. The financial attractiveness of raising price above the competitive level depends on the trade-off of higher prices on the sold quantity versus lost sales due to the increased price. It is clear that the payoff in non-competitive market is greater if raising prices has a smaller impact on sales.

When the retail price of electricity does not vary over time, a wholesale seller's attempt to exercise market power and raise wholesale prices has no short-run impact on quantity since end-use customers do not see a change in the retail price. This makes it much more profitable for the wholesale seller to exercise market power. With time-varying prices that reflect changes in the wholesale price, an attempt to raise wholesale prices will impact retail prices and thus reduce the quantity of power that customers demand. This customer response reduces the profitability of raising wholesale prices and, thus, discourages the exercise of market power.

Without time-varying retail prices, the combination of supply-demand mismatches and the ability of sellers to exercise market power at peak times creates a relationship between price and system load that looks like a hockey stick laid on its side. Figure 4.3 shows a price/load scatterplot for California during June 2000 and a polynomial curve fitted to the points. The hockey-stick relationship is a fairly constant price over a wide range of outputs and then steeply upward-sloping price as demand grows closer to capacity. Time-varying prices would reduce the frequency and degree of price spikes during periods of high system load.

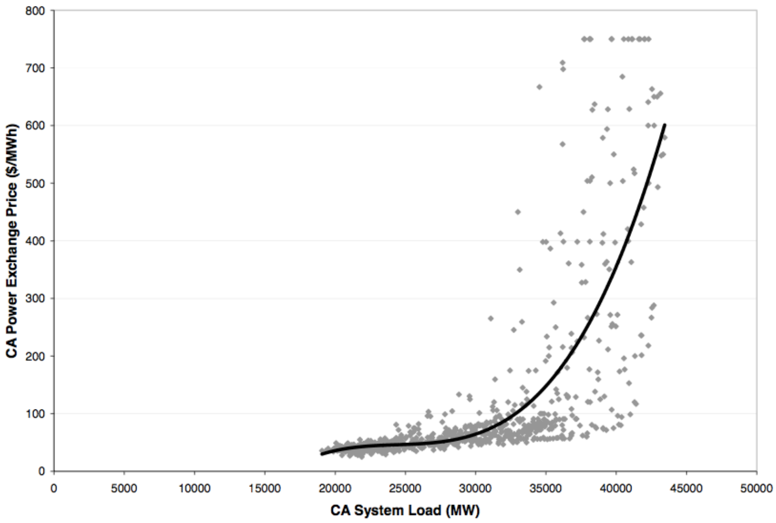


Figure 4.3 California Power Exchange Price versus System Load – June 2000 [10]

4.3 Forecasting Hourly Electricity Price

In Section 4.4, a retail electricity-pricing model is proposed. This electricity-pricing model consists of two variables: base price and price gap. Base price is wholesale electricity prices dependent on APX-Endex. Forecasting hourly electricity prices is an important tool for the proposed electricity-pricing model so then retailers can send the prices day-ahead or hour-ahead to the household customers. Better forecasting results are going to give better economic efficiency for the system. Before modelling our electricity-pricing scheme, it is important to forecast hourly electricity prices of wholesale market.

Price modelling and forecasting has long been at the centre of commodity and financial markets. Depending on the objectives of the analysis, a number of methods for modelling price dynamics have been proposed, ranging from parsimonious stochastic models to fundamental and game theoretic approaches.

Electricity spot price modelling and forecasting techniques generally can be traced back to models that originate either in electrical engineering or in finance. The various approaches that have been developed to analyse and predict power markets' behaviour and the resulting electricity prices may be broadly divided into six classes [85]:

- <u>Production-cost models:</u> These models simulate the operation of electricity generation at minimum cost. They have the capability to forecast prices on an hour-by-hour level; however they ignore the strategic bidding practices, including execution of market power. This model is not well suited for the recently established competitive markets.
- <u>Game theoretic approaches:</u> These models take strategic bidding into considerations, however a number of components have to be defined: the players (utilities), their potential strategies, the ways they interact and the set of payoffs, which is not suitable for short-term price forecasting.

- Fundamental methods: These methods describe price dynamics by modelling the impact of important physical and economic factors on the price of electricity [13], [74]. The fundamental data such as loads, weather conditions, system parameters, etc. is used. Because of the nature of fundamental data, which is typically collected over longer time intervals, data availability is an issue. Pure fundamental models are better suited for medium-term rather than short-term predictions. Some recent examples include [63] and [23].
- Quantitative models: These models characterise the statistical properties of electricity prices over time for evaluating the derivatives and risk management. Consequently, these models are not required to accurately forecast hourly prices but to recover the main characteristics of electricity prices in particular, seasonality, mean-reversion, high volatility and the occurrence of spikes, typically at the daily time scale.
- Statistical analysis: These are direct applications of the statistical techniques of load forecasting or econometric implementations for power market. Statistical analysis stand a better chance in efficient and useful forecasting in power markets then in financial markets. The reason for this is the seasonality in electricity price processes. It makes the electricity prices more predictable than those of "very randomly" fluctuating financial assets.
- Artificial intelligence-based techniques: AI-based models tend to be flexible and can handle complexity and non-linearity. This makes them promising for short-term predictions and a number of authors have reported their excellent performance in short term price forecasting (STPF). Artificial neural networks (ANNs) have probably received the most attention [91]. Other non-parametric techniques have been also applied, however, typically in hybrid constructions [68].

Of the six above-mentioned approaches, statistical analysis and AI-based models are best suited for STPF, in particular at the hourly time horizon. Statistical analyses are chosen in this thesis. The choice is backed by results of a recent study by [20], which compared different methods of short term price forecasting: time series analysis, ANNs and wavelets. The ANN technique was the worst outcome of the five tested models. Consequently, in this chapter statistical approaches are utilised.

4.3.1 Time Series Data

Collections of observations of a variable that become available sequentially through time are called time series data [11]. The order of observations is represented by a subscript t. Therefore, p_t is t th observation of time t and a proceeding observation is written as p_{t-1}, and succeeded observation as p_{t+1}.

In most electricity markets the series of prices presents the following features:

1. High Frequency
2. Non-constant mean and variance
3. Daily and weekly seasonality
4. Calendar effect on weekend and holidays
5. High volatility
6. Presence of outliers

These characteristics, which can be observed in the hourly price series of APX-Endex (APX-ENDEX, 2012) from 01.01.2009 to 12.02.2012, give non-stationary character for the time series. The analysis of the time series demands the series to be stationary. The stationarity of a time series is related to its statistical properties in time. That is in the more strict sense, a stationary time series exhibits similar "statistical behaviour" in time and this is often characterized as a constant probability distribution in time [54]. If the process has the mean, variance and autocorrelation structure constant over time then process is known as stationary process.

Following actions are being taken on our data:

- The high frequency and high volatility features are characteristics inherent to the series that cannot be changed.
- The non-constant mean feature of the price series is alleviated by the differentiating the original series by 1 hour before data (hourly differentiation), 24 hour before data (daily differentiation), 168 hour before data (weekly differentiation) or other values depending on the series. This has been treated in Section 4.3.2 in detail. The non-constant variance is alleviated by taking logarithms of prices.
- Daily and weekly seasonalities are typically taken into account through the use of seasonality models of orders 24 and 168, respectively. The calendar effect is taken into account by incorporating ad-hoc logic. This will be shown in Section 4.3.2 in detail.
- Outliers have been explicitly treated. Missing values and outliers were substituted by the arithmetic average of the two neighbouring values and negative values were substituted with forecasts for those hours as suggested in [85].

4.3.2 Model

In this section, only one model based on time series analysis is presented: Dynamic Regression (DR). This model is selected after reviewing following scientific articles: [20], [85] and [86]. [20] compares time series models of ARIMA, dynamic regression, transfer function and concludes that the dynamic regression and transfer function algorithms are more effective than ARIMA models. Weron, in [85] and [86], compares the models included different specifications of linear autoregressive time series with heteroscedastic noise and/or additional fundamental variables and concludes that the best results were obtained using the dynamic regression.

The description of the standard statistical methodology to construct a model is presented below [20]:

Step 0. A class of models is formulated assuming certain hypotheses
Step 1. A particular model is identified for the series being considered
Step 2. The parameters of the model are estimated
Step 3. If the hypotheses of the model are validated, the procedure continues in Step 4.; otherwise the procedure continues in Step 1. to refine the model
Step 4. The model is used to forecast

Conventional and commercially available software such as Eviews can be used to carry out the actual prediction in a convenient manner.

Step 0. Model Selection: Dynamic Regression Model

[87] investigates the forecasting power of various time series models for electricity spot prices. The models included different specifications of linear autoregressive time series with heteroskedastic noise and/or additional fundamental variables. Further, a non-linear, Markov regime-switching model with AR(1)-type processes as well as threshold regime-switching models (TAR and TARX) were considered. The models were tested on a time series of hourly system prices and loads from the California power market. The best results were obtained using a non-linear TARX model and a relatively simple ARX model [87].

Autoregressive Model with Exogenous Variable or Dynamic Regression (ARX)

The autoregressive model is expressed as the current value of a variable p_t depends only upon the value that the variable took in previous periods plus an error term. An autoregressive model is denoted by $AR(r)$, where r is the order of the process and the order of the process represented number of parameters that need to be estimated. An r th order autoregressive process is written as

$$p_t = C + \phi_1 p_{t-1} + \phi_2 p_{t-2} + \ldots + \phi_r p_{t-r} + \varepsilon_t$$

where p_t is the series and C is constant. Also, $\phi_1, \ldots, \phi_r$ are the autoregressive parameters which describe the effect of a unit change in two consecutive time series observations (p_{t-1} on p_t) and which need to be estimated. The ε_t term is a white noise or error term assumed to be independent and identically distributed (i.i.d) with mean zero and variance constant over time, $\varepsilon_t \sim N(0, \sigma^2)$ and zero autocorrelation.

The autoregressive model with exogenous variable $v_1, v_2, \ldots, v_k$, or dynamic regression model is denoted by $ARX(r, g_1, \ldots, g_k)$ where g_i's are the orders of the exogenous factors (e.g. system load, temperature, power plant availability). The autoregressive model with one exogenous variable can be written [20] as

$$p_t = C + \phi_1 p_{t-1} + \phi_2 p_{t-2} + \ldots + \phi_r p_{t-r} + \psi_1 v_{t-1} + \psi_2 v_{t-2} \ldots + \psi_r v_{t-r} + \varepsilon_t$$

Step 1. Model Identification

The target of this step is to identify which polynomial parameters should be estimated, because they affect the forecasting. The initial selection is based on the observation of the autocorrelation and partial autocorrelation plots. Further refinement of the selection is based on physical knowledge and on engineering judgment.

Logarithmic Function of Prices

In this step, it might be convenient to make the time series stationary (constant mean and variance). To that end, a transformation of the original price data may be necessary. A logarithmic transformation is usually applied to the price data to attain a more stable variance.

Price P_t and load L_t is transformed in logarithmic value to attain more stable variances in the model result.

$p_t = \log(P_t)$

$l_t = \log(L_t)$

Choice of Lags

The best-forecast results were obtained for pure ARX (autoregressive model with exogenous variable) model is given by [85]. The optimal AR (autoregressive) structure, i.e. yielding the smallest forecast errors for the first week of the test period was found to be the variable set of last two days log-price p_{t-24} and p_{t-48}, last week log-price p_{t-168} and the minimum of previous day's 24 hourly log-prices (mp_t) [85].

$$p_t = C + \phi_1 p_{t-24} + \phi_2 p_{t-48} + \phi_3 p_{t-168} + \phi_4 mp_t$$

However a small change has been made in this model, in case of using the minimum of previous day's 24 hourly log-price, previous hour's log price is implemented in the model. One of the reasons for this improvement is, it is simpler to apply in.

$$p_t = C + \phi_1 p_{t-24} + \phi_2 p_{t-48} + \phi_3 p_{t-168} + \alpha_1 p_{t-1}$$

Exogenous Variable and Dummies

Next hour forecasted load is chosen as exogenous parameter. This is because of the good forecast performance of this parameter in previous electricity forecasting literature.

This simple model was unable to cope with the weekly seasonality. Weekly seasonality was causing the forecast results on Mondays, Saturdays and Sundays to be worse then the rest of the week. Inclusion of three dummy variables Saturday (D_{sat}), Sunday (D_{sun}) and Monday (D_{mon}) and next day forecasted load helped a lot. The best model structure, in terms of forecasting performance for the first week of the test period, turned out to be:

$$p_t = C + \phi_1 p_{t-24} + \phi_2 p_{t-48} + \phi_3 p_{t-168} + \alpha_1 p_{t-1} + \psi_1 l_t + d_1 D_{sat} + d_2 D_{sun} + d_3 D_{mon} + \varepsilon_t$$

Forecasted price is given by the equation above: ψ_1 is the coefficient of the logarithm of next hour forecasted load (l_t); d_1, d_2, d_3 are the coefficients of dummies.

Step 2. Polynomial parameter estimation

Once the parameters of the polynomials different from 0 have been identified (through plot observation, physical knowledge and engineering judgment), these parameters should be estimated. The estimation procedure is based on available historical data. Good estimators are found assuming that the data constitute observations of a stationary time series and maximizing the likelihood function with respect to the polynomial parameters.

Sometimes, the series contain unusual observations, or outliers. In these cases, it is appropriate to use a procedure to detect and minimize the effect of these outliers. With this adjustment, better forecasting performance is usually achieved. Missing values and outliers were substituted by the arithmetic average of the two neighbouring values and negative values were substituted with forecasts for those hours as suggested in [85].

An econometric analysis program Eviews 7 is used to estimate the parameters, parameters are given in Table 4.1.

Table 4.1 Parameters of Forecasting Model

Variable	Coeffiecient	p-Value
c	0.7709	0.0000
α_1	0.8444	0.0000
ψ_1	-0.0215	0.0001
d_3	-0.0065	0.0343
d_1	-0.0226	0.0000
d_2	-0.0504	0.0000
ϕ_1	0.2951	0.0000
ϕ_2	0.1333	0.0000
ϕ_3	0.3956	0.0000

Step 3. Validation of model hypotheses

In this step, a diagnosis check is used to validate the model assumptions. If the estimated model is appropriate, then the residuals (actual prices minus predicted prices) should behave in a manner consistent with the model. Residuals must satisfy the requirements of a white noise process: zero mean, constant variance, zero correlation and normal distribution. Taking tests for randomness, such as the one based on the Ljung-Box statistics and observing plots, such as the autocorrelation and partial autocorrelation plots, allow checking of these requirements.

If the hypotheses on the residuals are validated, then the corresponding model can be used to forecast prices and this step is concluded successfully. Otherwise, the residuals contain a certain structure that should be analysed to refine the model, and the procedure continues back in Step 1. To refine the model a careful inspection of the autocorrelation plots of the residuals should be performed.

Step 4. Actual prediction

In this step, the corresponding model from Step 2 is used to predict future values of prices, typically 24 hours ahead. It should be noted that prediction quality deteriorates as the predicted hour increases, i.e., the error of the estimate of hour 24 is typically greater than the error of the estimate of hour 1.

4.3.3 Forecast Error Measures

The most widely used measures of forecasting accuracy are those based on absolute errors, absolute values of difference between the actual, P_t, and predicted, $\hat{P}_t$, prices for a given hour, t. Another popular measure is the Mean Absolute Error (MAE); for hourly prices P_t the daily MAE is given by

$$MAE_{daily} = \frac{1}{24}\sum_{t=1}^{24}\left|P_t - \hat{P}_t\right|$$

Sometimes no the absolute, but the relative or percentage difference is more informative. For instance, when comparing results for two distinct data sets. In such cases the Mean Absolute Percentage Error (MAPE) is preferred. For hourly prices P_t the daily MAPE is given by

$$MAPE_{daily} = \frac{1}{24}\sum_{t=1}^{24}\frac{\left|P_t - \hat{P}_t\right|}{P_t}$$

The MAPE measure works well in load forecasting, since the actual load values are rather large. However when applied to electricity prices, MAPE could be misleading. In particular, when prices drop to zero, MAPE values become very large regardless of the actual absolute differences $\left|P_t - \hat{P}_t\right|$. The reason for this is the normalisation by the current price P_h.

Alternative normalisation is proposed here; the absolute error $\left|P_t - \hat{P}_t\right|$ is normalised by the average price attained during the day. The resulting measure, also known as the Mean Daily Error (MDE), is given by

$$MDE = \frac{1}{24}\sum_{h=1}^{24}\frac{\left|P_h - \hat{P}_h\right|}{\bar{P}_{24}} = \frac{1}{\bar{P}_{24}} MAE_{daily}$$

Here, $\bar{P}_{24} = \frac{1}{24}\sum_{h=1}^{24} P_h$. In general, MDE compared to MAPE puts more weight to errors in the high-price range. Analogously to MDE, the mean weakly error (MWE) can be computed as:

$$MWE = \frac{1}{168}\sum_{h=1}^{168}\frac{\left|P_h - \hat{P}_h\right|}{\bar{P}_{168}} = \frac{1}{\bar{P}_{168}} MAE_{weekly}$$

Results

Daily results and graphs are given in the Appendix A. Here, only the weekly mean absolute error and mean weekly error for weeks between 16.01.2012 and 06.02.2012 is given in Table 4.2.

Table 4.2 Weekly Mean Absolute Error and Mean Weekly Error for weeks between 16.01.2012-06.02.2012

Forecasted Period	APX weekly	MAE weekly	MWE
16.01-22.01	44.66184524	2.284793008	0.051157604
23.01-29.01	46.04309524	2.069306943	0.044942829
30.01-05.02	53.89136905	3.774173922	0.070032994
06.02-12.02	73.22303571	6.582462888	0.089896067

4.4 Proposed Electricity Pricing Model

In this thesis, the following electricity-pricing model is proposed to motivate household consumers to shift their loads to off-peak hours. Retail electricity price ϕ_t is given by the sum of base price p_t and the price gap ρ_t.

$$\phi_t = p_t + \rho_t$$

4.4.1 Base price

Here the base price is defined as marginal cost of generating electricity by authors [16], [55]. [16] defines base price as the wholesale price: $p_t = \frac{C_t(r_t)}{r_t}$.

In this formula, r_t in kW is the predetermined total daily energy demand of all users (residential, commercial, industrial and transportation) for time slot t and forms the vector $R = [r_1, r_2, \ldots, r_t]$ for the time horizon. $C_t(r_t)$ is the cost function, which is assumed to be a decreasing and strictly convex function of r_t; and thus ϕ_t is higher during high load periods than during low load periods.

Instead of [16] and [55]'s definition of base price, forecasted APX-Endex prices are used as base price in this thesis. In previous Section 4.3, APX wholesale prices explained and are forecasted for next-hour.

4.4.2 Price Gap

The price gap ρ_t is designed to influence the difference between the actual residential demand and the initial or predetermined average daily demand of residential users. ρ_t is designed such that ρ_t increases when the difference between the actual demand and the predetermined average daily $\delta_t = q_t - \overline{q}$ increases. Here q_t and $\overline{q}$ are given as follows

$$q_t = \sum_{i=1}^{N} u_i^t + x_i^t \qquad \overline{q} = \frac{\sum_{t=1}^{T} q_t}{T}$$

On the left formula, x_i^t is the "shiftable" and u_i^t is the "non-shiftable" power consumption of user at time slot t.

Smaller δ_t, the lower price gap ρ_t, so that the energy scheduler is more willing to schedule the appliance to operate during this period, and vice versa. Price gap can be designed as follow

$$\rho_t = e^{\mu(q_t - q_{average})}$$

where $\mu > 0$ is a design parameter and is independent of time. Exponential function is a strictly convex function, which gives positive range for all domains. If δ_t increases, the price gap will increase and the retail price set by the energy provider becomes higher. This encourages users to consume more energy to reach the average value. From this pricing mechanism, one can see that this encourage users schedule their energy consumption in such a way that the energy demand is more equally over all time slots.

4.4.3 Validation of Pricing Scheme

In Section 4.1, retail electricity pricing scheme in the Netherlands is summarized. If a household makes electricity contract for 1-year period, he/she will pay the fixed amounts given below:

Table 4.3 Electricity prices of retail suppliers in The Netherlands

Suppliers	Delivery Cost excluding BTW (cents/kWh)
Essent	7.22
e.on	7.04
Eneco	7.88
NUON	7.04

Let's compare these prices to the proposed pricing model. Hourly APX prices of 16.01.2012 are used as base price. On the top of this base price, price gap is added; design factor μ is selected as to make the proposed pricing model close to the electricity prices of retail suppliers in The Netherlands. Hourly retail electricity prices of proposed pricing model can be found in the Appendix B. Daily average electricity price according to the proposed pricing scheme is 6.848 cents/kWh. Proposed electricity pricing scheme shows less than %10 difference compared to 1-year contract prices offered in the Netherlands. Since 1-year contract prices are calculated by price predictions of the duration, example of daily average electricity price is acceptable.

Below in the Figure 4.4, hourly electricity consumption of 25 houses is shown. It can be seen clearer from the graph how the proposed electricity scheme works.

More the electricity consumption is deviating from average electricity demand, more the price gap affects electricity price.

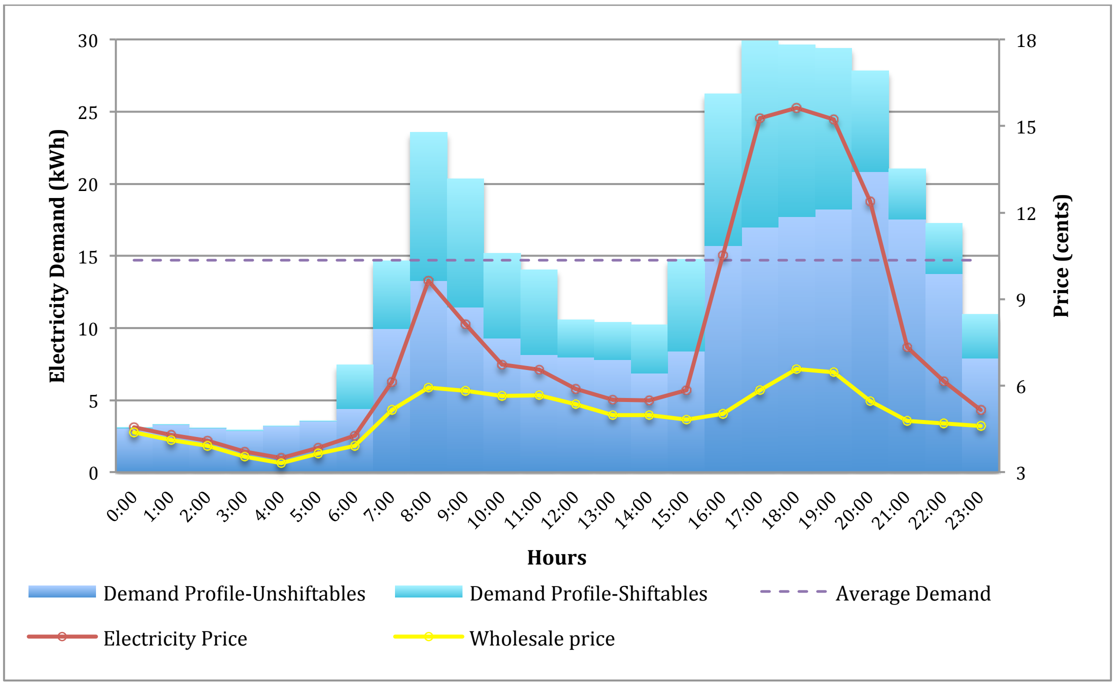


Figure 4.4 Hourly shiftable and unshiftable electricity demand and electricity prices without ECS deployment

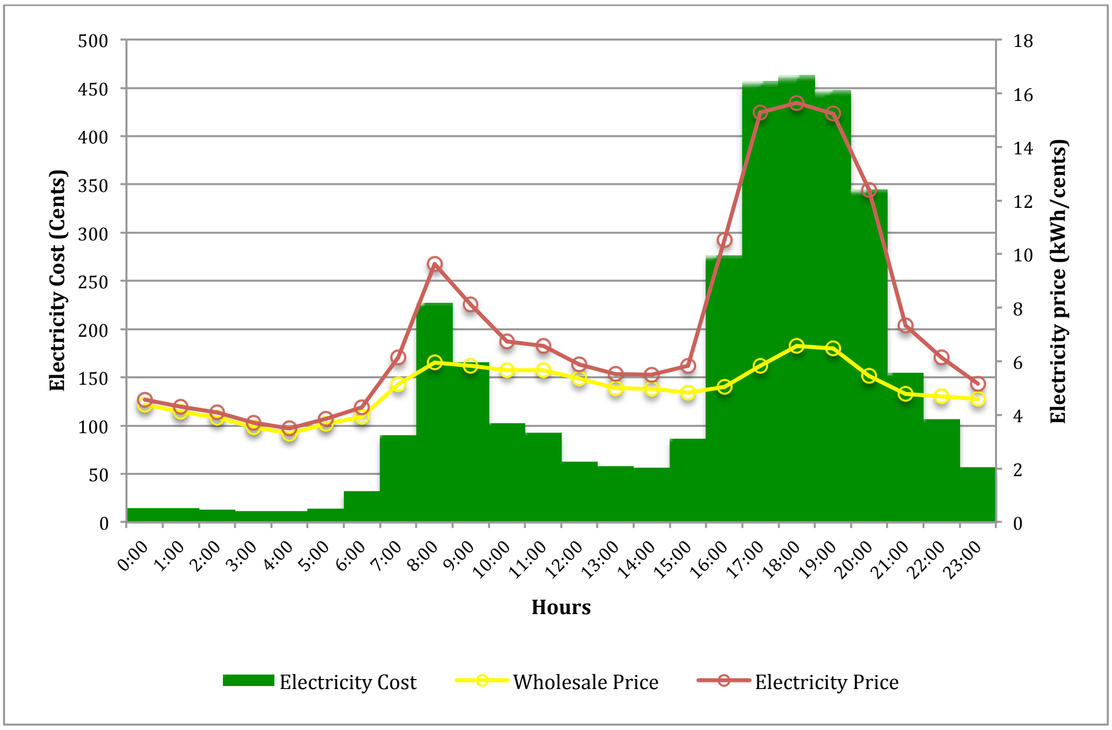


Figure 4.5 Hourly energy cost of 25 houses without ECS deployment

5 Electricity Consumption Scheduling

Smart grid is a power network composed of intelligent nodes that can operate, communicate, and interact, autonomously, in order to efficiently deliver power and electricity to their consumers. This multi-task characteristic of the smart grid motivates the adoption of advanced techniques for overcoming the various technical challenges at different levels such as design, control, and implementation. In this respect, game theory is expected to constitute a key analytical tool in the design of the future smart grid.

5.1 Game Theory and Demand-Side Management

Game theory is a formal analytical as well as conceptual framework with a set of mathematical tools enabling the study of complex interactions among independent rational players. For several decades, game theory has been adopted in a wide number of disciplines ranging from economics, laws and politics to psychology. More recently, game theory has also become a central tool in the design and analysis of communication systems.

The proliferation of advanced technologies and services in smart grid systems implies that disciplines such as game theory will naturally become a prominent tool in the design and analysis of smart grids. In particular, there is a need to deploy novel models and algorithms that can capture the following characteristics of the emerging smart grid:

- The need for distributed operation of the smart grid nodes for communication and control purposes
- The heterogeneous nature of the smart grid, which is typically composed of a variety of nodes such as micro-grids, smart meters, appliances, and others, each of which having different capabilities and objectives
- The need for efficiently integrating advanced techniques from power systems, communications, and signal processing.
- The need for low-complexity distributed algorithms that can efficiently represent competitive or collaborative scenarios between the various entities of the smart grid. In this context, game theory could constitute a robust framework that can address many of these challenges [69].

5.1.1 Introduction and Basic Game-Theoretic Concepts

Game theory is a mathematical framework that can be divided into two main branches: non-cooperative game theory and cooperative game theory.

Non-cooperative game theory can be used to analyse the strategic decision making processes of a number of independent players, that have partially or totally conflicting interests over the outcome of a decision process which is affected by their actions. Essentially, non-cooperative games can be seen as capturing a distributed decision making process that allows the players to optimize, without any coordination or communication, objective functions coupled in the actions of the involved players. It is noted that the term non-cooperative does not always imply that the players do not cooperate, but it means that, any cooperation that arises must be self-enforcing with no communication or coordination of strategic choices among the players.

Basics of Non-cooperative Game Theory:
Non-cooperative games can be grouped into two categories: static games and dynamic games. Static games are games in which the notions of time or information do not affect the action choices of the players. Thus, in a static setting, a non-cooperative game can be seen as a one-shot process in which the players take their actions only once (simultaneously or at different points in time). In contrast, dynamic games are games in which the players have some information about each others' choices, can act more than once, and time has a central role in the decision making. For static games, one general definition is the following:

Definition 1: A static non-cooperative game is defined as a situation that involves three components: the set of players N, the action sets $(\mathcal{A}_i)_{i\in N}$, and the utility functions $(u_i)_{i\in N}$. In such a non-cooperative game, each player i wants to choose an action $a_i \in \mathcal{A}_i$ so as to optimize its utility function $u_i(a_i, a_{-i})$ which depends not only on player i's action choice a_i but also on the vector of actions taken by the other players in $N \setminus \{i\}$, denoted by a_{-i}.

Note that, when the game is dynamic, one needs to also define, as part of the game, additional components such as information sets, time, or sets of past actions, which are usually reflected in the utility functions. It is noted that the notion of action coincides with that of a *strategy* in static games while in dynamic games strategies are defined, loosely, as functions of the information available to each player.

The strategy choices of the players can be made either in a deterministic manner such as *pure strategies,* or by following a certain probability distribution over the action sets $(\mathcal{A}_i)_{i\in N}$ such as *mixed strategies.*

Solution Concept:
The objective of non-cooperative game theory is to provide algorithms and techniques suitable for solving such optimization problems and characterizing their outcome, notably when the players are making their action choices non-cooperatively without any coordination or communication. One of the most important solution concepts for game theory in general and non-cooperative games in particular is that of a *Nash equilibrium.*

The Nash equilibrium characterizes a state in which no player i can improve its utility by changing *unilaterally* its strategy, given that the strategies of the other players are fixed. For a static game, the Nash equilibrium in pure strategies can be formally defined as follows:

Definition 2: A *pure-strategy Nash equilibrium* of a static non-cooperative game is a vector of actions $a^* \in \mathcal{A}$ ($\mathcal{A}$ is the Cartesian product of the action sets) such that $\forall i \in N$, the following holds:

$$u_i(a_i^*, a_{-i}^*) \geq u_i(a_i, a_{-i}), \ \forall a_i \in \mathcal{A}_i$$

In mixed strategies, a Nash equilibrium is defined similar to Definition 2 with the strategies being a vector of probability distributions over the action sets.

The Nash equilibrium serves as a building block for many types of non-cooperative games. This solution concept has both advantages and drawbacks. One of its main advantages is that it characterises a stable state of a non-cooperative game in which no player $i \in N$ can improve its utility by unilaterally changing its action a_i given that the actions of the others are fixed at a_{-i}^*. This state can often be reached by the players in a distributed manner and with little coordination.

However, the Nash equilibrium also has some drawbacks. For example, even in finite games, where each player has a finite action set, Nash equilibrium is only guaranteed to exist in *mixed strategies.* A non-cooperative game can also have multiple Nash equilibriums then selecting an efficient and desirable Nash equilibrium is a challenging topic.

Nonetheless, several metrics such as the price of anarchy or the price of stability can be used to study the efficiency the Nash equilibrium such as in [56]. Moreover, the Nash equilibrium concept can be complemented and extended using many other game theoretic techniques such as pricing so as to provide suitable solutions for non-cooperative games.

Cooperative Games:

In non-cooperative games, it is assumed that the players are unable to coordinate or communicate with one another directly. However, for games in which the players are allowed to communicate and to receive side payments (share utilities), it may be of interest to adopt fully cooperative approaches. In this respect, *cooperative game theory* provides frameworks that can answer one pertinent question: "What happens when the players can communicate with one another and decide to cooperate?"

Cooperative games allow investigating how one can provide an incentive for independent decision makers to act together as one entity so as to improve their position in the game. For example, in politics, different parties may decide to merge or coalesce into a cooperative group so as to improve their chances in obtaining a share of the power.

Cooperative game theory encompasses two parts: Nash bargaining and coalitional game. Nash bargaining deals with situations in which a number of players need to agree on the terms under which they cooperate while coalitional game theory deals with the formation of cooperative groups or coalitions. In essence, cooperative game theory in both of its branches provides tools that allow the players to decide on whom to cooperate with and under which terms given several cooperation incentives and fairness rules.

5.1.2 Learning in Games

While studying the efficiency of equilibrium is central to game-theoretic design, another important aspect is to develop learning algorithms that enable the players to reach a certain desired game outcome. In fact, choosing the desired equilibrium is a challenging. To reach certain equilibrium, the players must follow well-defined rules that enable them to observe the current game state and make a decision on their strategy choices. Essentially, a learning scheme is an iterative process in which each iteration involves three key steps performed by every player [90]:

- Observing the environment and current game state,
- Estimating the prospective utility, and
- Updating the strategy based on the observations.

Numerous learning algorithms have been proposed in the literature. The simplest of such algorithms is the so-called *best response dynamics,* which is an iterative process in which a player selects the strategy that maximizes its utility at every iteration. Several variants of this process exist. One of the advantages of a best response algorithm is its simple implementation, however, it suffers from several drawbacks. First, a best response process is only guaranteed to converge to equilibrium for certain types of utility functions. Second, best response dynamics are highly sensitive to the initial conditions and any changes in these conditions could lead to different equilibriums. Third, adopting a best response approach does not always guarantee convergence to an efficient equilibrium [33].

5.1.3 Game Theory and Demand-Side Management

Game theory has been extensively used for demand-side management and demand-response models in smart grids such as in [12], [16], [38], [51], [52] and [55].

[12] proposes a game theoretical decision-making scheme for electricity retailers with real-time DSM in the smart grid. Dynamic behaviours of customers is modelled by utility functions and then later suggests a four-stage Stackelberg game to model interactions between a retailer and its customers.

[51] proposes a computationally feasible and automated optimization-based residential load control scheme in a retail electricity market with real-time pricing tariff combined with inclining block rates.

[52] proposes a game theoretical model in order to minimize the cost of energy and also to balance the total residential load when multiple users share a common energy source. The authors used game theory to model DSM problem in smart grid where customers schedule their energy consumption profiles to minimize the total energy payment. However, all users need to exchange their energy consumption profiles to each other, which is not practical. In practice, users are only able to communicate and exchange information with energy providers.

[55] proposes a game theoretic framework to model independent decision-making of users' energy consumption scheduling. The aim of the authors is to reduce the peak load of the system. A new pricing model is designed and a distributed algorithm is proposed to achieve Nash equilibrium of the non-cooperative game in which each user tries to minimize its energy payment to an energy provider.

[16] applies Stackelberg game to model DSM problem where a retailer act as a leader and customers act as followers. The best provider and customers' strategies are given and a distributed algorithm has been proposed where the link between the leader and followers is the price signal.

In this paper, unlike [52], it is assumed that users are only able to communicate and exchange information with the retailer. So then, a similar Stackelberg game theoretical model of [16] is proposed.

In order to provide a better overview on how game theory can be applied for demand-side management, in this section, we start by analysing a non-cooperative game approach for modelling the interactions between a number of consumers and an energy generator or substation.

5.1.4 Game Theory for Demand-Side Management through Energy Consumption Scheduling

Introduction and Model:

Classical demand-side management schemes such as direct load control and smart pricing are focused on the interactions between a utility company and each individual end-user. On the one hand, direct load control enables the utility company to control the appliances inside the home of each individual consumer, based on a certain agreement. On the other hand, the essence of smart pricing is to provide monetary incentives for the users to voluntarily shift their consumption and balance the load on the electricity grid. While these schemes have been extensively deployed, they are all focused on the individual user energy. However, [52] shows that, instead of focusing only on the individual user consumption such as in classical schemes, it is better to develop a demand-side management approach that optimizes the properties of the aggregate load of the users. This is enabled by the deployment of communication technologies that allow the users to coordinate their energy usage, when this is beneficial.

Similar to [52], a power system with N users and a single energy source, such as a substation. A wired or wireless technology interconnects the smart meters and the sources, hence, enabling them to communicate at any point in time. We let N denote the set of all users. Assuming time is slotted into hour-long intervals, at any given hour h the total consumption of all users is denoted by $L_h = \sum_{i \in N} l_i^h$, with l_i^h being the energy consumption of user i at hour h.

This total consumption incurs a cost on the utility company, which could reflect either a physical cost (i.e., costs for thermal generators) or a virtual cost that is used by the utility company so as to encourage an energy-aware behaviour by the users. Practical cost functions such as thermal generation costs are increasing with the load and, often, strictly convex. As a result, let $\sum_{h=1}^{H} C_h(L_h)$ denote the total cost incurred on the utility company over a period of H hours by all N users with the cost function $C_h(.)$ being a strictly convex and increasing function. Note that, for a certain load value, the cost function $C_h(.)$ could lead to different costs depending on the hour during which this load is consumed.

Based on the cost $\sum_{h=1}^{H} C_h(L_h)$, the utility company would decide on how much to charge the users for the consumption during the H hours. The dependence of the cost function on the total users' load L_h implies that a change in the load of one user would impact the total cost of the utility company, which, in turn, impacts the individual charges of the users. Hence, clearly, the users can be seen as independent decision makers whose choices of scheduling times and loads would impact one another. In this model, the objective is to enable the smart meters at the users premises to utilise automatic energy consumption schedulers so as to choose when to schedule appliances in order to minimize the total cost on the utility company and, subsequently, minimize the charges on each individual user. To address this problem, a game theoretic formulation is suitable as shown in [52] and discussed next.

A Non-cooperative Game for Scheduling Appliances:
Essentially, we are interested in devising a demand-side management scheme that enables to schedule the *shiftable* appliances such as dish washers, washing machines and dryers, while minimising the overall energy consumption and, thus, the charges on the consumers.

In this context, as in [52], we can formulate a static non-cooperative game in which the set of users N represents the players with the strategy of every player $i \in N$ being a vector x_i which is formed by stacking up energy consumption schedule vectors of the form $\mathrm{x}_i = \left[x_{i,a}^{1} .. x_{i,a}^{H} \right]$ where $x_{i,a}^{h}$ is the energy consumption scheduled for an appliance a by user i.

In this non-cooperative game, each user i needs to select its vector x_i so as to optimize a utility function $u_i(\mathrm{x}_i, \mathrm{x}_{-i})$, which is mainly a function of the cost function $C_h(.)$ at each time h. The exact expression of the utility depends on how the utility company performs the billing as well as on the type and energy requirement of the users' appliances. Exact expressions for this utility were derived in [52] under the assumption that each user is billed proportionally to its total consumption. In consequence, we have a static non-cooperative game, which we refer to as the *appliances scheduling game* and we can make several remarks on the properties of this game based on the results in [52], as follows:

1) Nash equilibrium for the appliances scheduling game always exists and all equilibriums coincide with the optimal scheduling policy that *minimises* the overall utility company cost, which is given by $\sum_{h=1}^{H} C_h(L_h)$.
2) The Nash equilibrium of the game corresponds to a *unique* set of total loads l_h^{NE} at each user $i \in N$.
3) Each user can map the total load $l_i^{h,NE}$ at the equilibrium to *any* feasible set of strategies x_i^{NE}. For the utility function considered in [52], the appliances are, thus, indifferent to when they are scheduled as every schedule would always correspond to the minimum of the total cost incurred on the utility company.

The authors in [52] propose an algorithm that uses best response dynamics to find the Nash equilibrium while ensuring that no user has an incentive to cheat and announce an incorrect energy schedule. A *best response* algorithm mainly relies on a sequence of decisions in which each player chooses the strategy that *maximises* its utility, given the current strategies of the other players. It is shown in [52] that, for the appliances scheduling game, best response dynamics always converges to equilibrium. The simulations in [52] also show that, whenever consumers have a good number of shiftable appliances, adopting a game-theoretic approach for scheduling these appliances can reduce the energy costs of up to 18% compared to existing solutions while also reducing the peak-to-average ratio of the energy demand (i.e., the ratio of the energy at peak hour to the average energy over a time period H) of about 17%.

Future Extensions of Game for Scheduling:
Clearly, using non-cooperative games can lead to smarter demand-side management schemes. The model studied in this sub-section can be extended in a variety of ways such as by:

- Introducing a utility function in which the time at which an appliance is scheduled impacts the payoff of the users. The objective of the game becomes to optimize a trade-off between minimizing the charges and optimizing the appliances' waiting time. By doing so, the properties and results of the game formulated in [52] are significantly impacted, although the non-cooperative framework is still useful to analyse the problem.
- Considering multiple energy sources and the interactions among them. In such a setting, hierarchical games such as Stackelberg games are a good candidate to provide insights on the appliances' scheduling problem.
- Studying a stochastic game counterpart of this model in which the smart meters schedule the appliances instantaneously based on the time-varying conditions of the network (e.g., the varying generation conditions of the energy source). The studied game can, in fact, constitute a building block for such a stochastic formulation. For instance, a stochastic game is essentially a dynamic game composed of a number of stages and in which, at the beginning of each stage, the game is in a specific state. In such a setting, the studied game and its solution can be used to solve or study each one of these stages. Hence, the studied game can serve as a single stage in a stochastic game setting (under both complete and incomplete information). Each one of these extensions leads to new challenges but also contributes to the

deployment of smart demand-side management schemes that account for the aggregate user loads as well as the individual objectives of the users.

5.2 Proposed Game Theoretical Model

5.2.1 System Model

Smart power system consists of one energy source provider and N load subscribers or users, as shown in Figure 5.1. The service provider buys electricity from the wholesale market and sells it to consumers. The energy scheduler in each home interacts with the service provider through an underlying two-way communication network (e.g., the smart metering infrastructure). The energy scheduler coordinates power use among in-home smart appliances; of particular interest in our model, it schedules the time of use of *shiftable* appliances within the home.

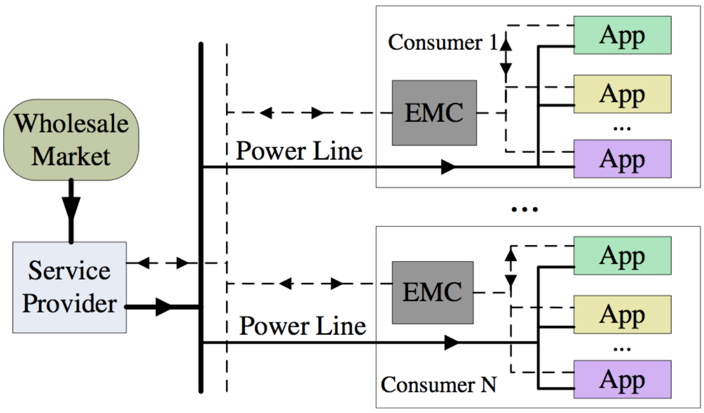


Figure 5.1 Household electricity market [16]

5.2.2 Household Consumption Profiles

In Chapter 3, the methodology of household consumption simulation is explained: [66] has built a 1-minute resolution household occupancy model, using a Markov-chain technique where the activity state in each household at each time step depends on the previous one, together with the probability of that state changing. The simulations are carried out for three persons in the house. Then, the time-use survey is used to predict the probability that the occupants in the house will change their activity, depending on what they happen to be doing at any one time. This in turn drives which electrical appliances are on and build a 1-minute resolution household demand profile model. 25 different simulations are run and the results are given below in the chart.

All 25 households are assumed to use the following “shiftable” and “non-shiftable” appliances.

Table 5.1 Appliances in Households

"Non-Shiftable"s		"Shiftable"s
Refrigerator	TV	Washing Machine
Freezer	TV receiver box	Dishwasher
Electric oven	VCR/DVD recorder	Dryer
Microwave oven	Computer	
Kettle	Printer	
Iron	CD player	
Vacuum cleaner	HiFi	
Alarm clock		

Figure 5.2 shows the cumulative 1-minute resolution total and "non-shiftable" electricity consumption and hourly total and "non-shiftable" electricity consumption of 25 households.

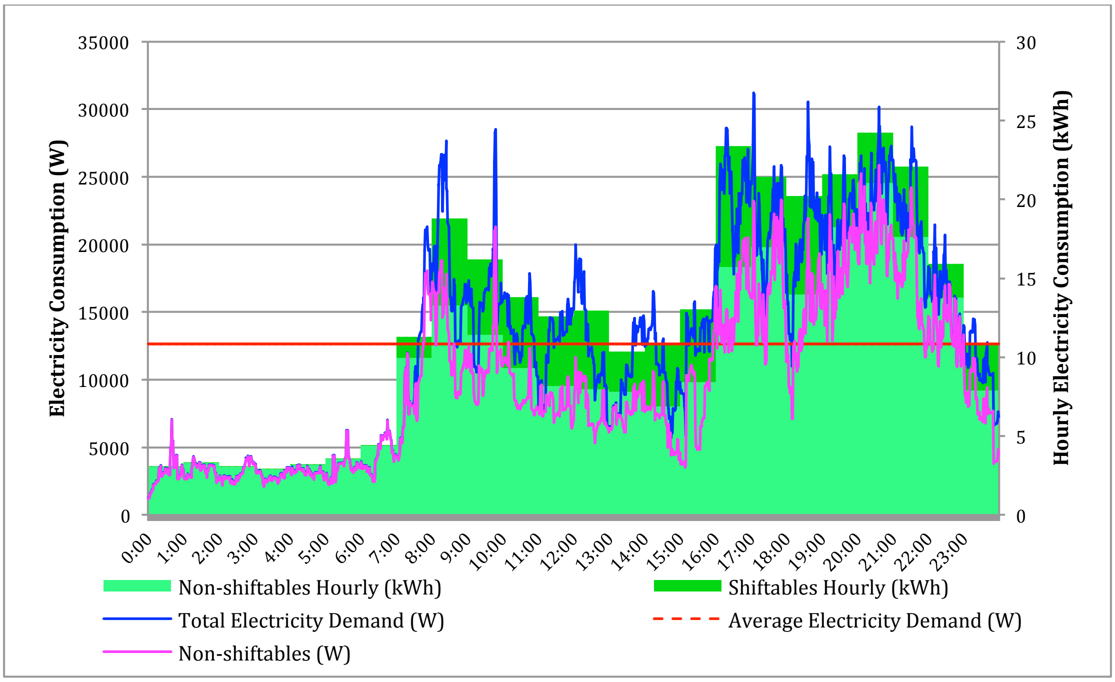


Figure 5.2 1-Minute Resolution of Electricity Demand Profile for 25 Households

Hourly consumption data of "non-shiftable" appliances are transformed from one-minute resolution consumption data. Hourly consumptions are calculated as follows; φ_m is the 1-minute electricity consumption in watts, average of every-minute electricity consumption in one hour gives q_i^t the power consumption of user $i \in N$ at time slot t in watt.hour.

$$q_i^t = \frac{\sum_{m=60t}^{m+60} \varphi_m}{60}$$

Let $\mathcal{N}$ be the set of users and $\mathcal{T}$ be the set of time slots, where $N \triangleq |\mathcal{N}|$ and

$T \triangleq |\mathcal{T}|$. For each user $i \in N$, the "non-shiftable" power consumption vector is defined $\mathrm{u}_i = \left[u_i^1, \ldots, u_i^t, \ldots, u_i^T\right]$ where u_i^t is the "non-shiftable" power consumption of user at time slot t. This "non-shiftable" power consumption vector is created for each user by [66] based data consumption profiler.

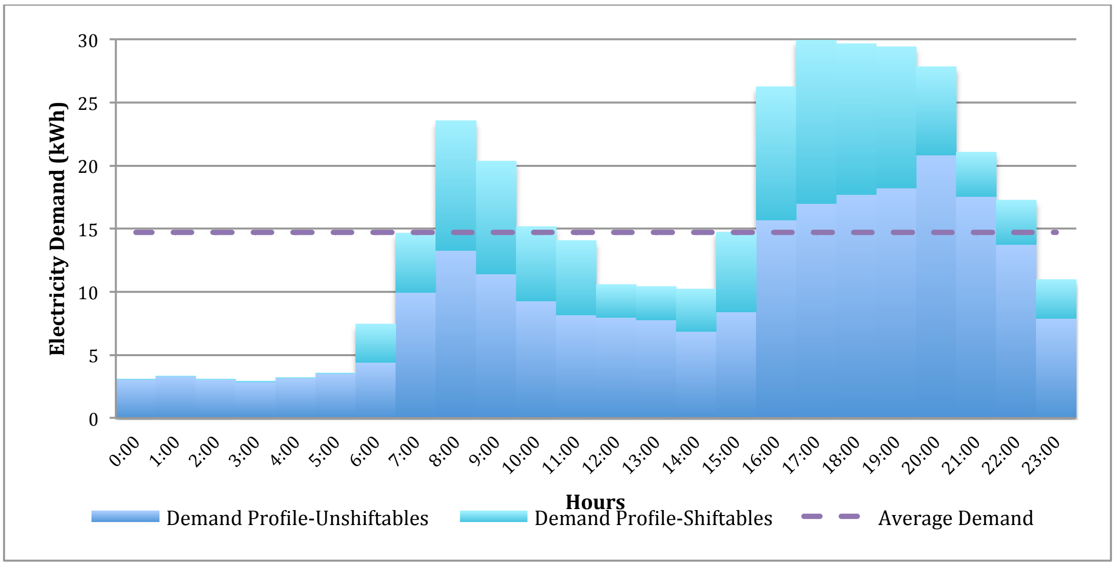
Once "non-shiftable" hourly consumption is obtained, operation durations and hourly consumption of "shiftable" appliances are calculated for each household and their average is given below Table 5.2.

Table 5.2 Operation duration and consumption of "shiftable" appliances

	Operation Duration $l_{i,a}$ **(Hours)**	**Hourly Consumption** $c_{i,a}$ **(kWh)**
Washing Machine	2	0.4634
Dishwasher	1	1.1860
Dryer	1	2.5500

Initial consumptions of these appliances are spread on every hour of the day on the basis of the Table 5.2. The initial consumptions of 25 households are given below Figure 5.3.

Figure 5.3 1-hour resolution of Electricity Demand for 25 households



The usage of shiftable appliance $a \in \mathcal{A}_n$, has three important features: start time s, operation duration $l_{i,a}$ and hourly consumption $c_{i,a}$. The initial start time of "shiftable" appliances are chosen to be similar to the first simulation results. Operation duration and hourly consumption of shiftable appliances are taken from [66].

Let $\mathcal{N}$ be the set of users and $\mathcal{T}$ be the set of time slots, where $N \triangleq |\mathcal{N}|$ and $T \triangleq |\mathcal{T}|$. For each user $i \in N$, given the scheduled start time s, $c_{i,a}$ and $l_{i,a}$, the service provider forms a "shiftable" power consumption vector $\mathrm{x}_{i,a} = \left[x_{i,a}^{1}, \ldots, x_{i,a}^{t}, \ldots, x_{i,a}^{T} \right]$ in kWh for this appliance, where

$$x_{i,a}^{t} = \begin{cases} c_{i,a}, & t \in \left[s, s + l_{i,a} \right) \\ 0, & t \in \mathcal{T} \setminus \left[s, s + l_{i,a} \right) \end{cases}$$

Power consumption vector of all the shiftables are shown as following formula

$$x_{i}^{t} = \sum_{a \in \mathcal{A}} x_{i,a}^{t}$$

5.2.3 Energy Consumption Scheduler

The ECS aims to minimize the cost to the consumer for the usage of the "shiftable" appliance $a \in \mathcal{A}_n$. Its action is to determine the optimal start time s for a shiftable appliance that was requested to turn on at time slot t_0.

Given the scheduled start time s, $c_{i,a}$ and $l_{i,a}$, the service provider forms a power consumption vector of a "shiftable" appliance $\mathrm{x}_{i,a} = \left[x_{i,a}^{1}, \ldots, x_{i,a}^{t}, \ldots, x_{i,a}^{T} \right]$, where

$$x_{i,a}^{t} = \begin{cases} c_{i,a}, & t \in \left[s, s + l_{i,a} \right) \\ 0, & t \in \mathcal{T} \setminus \left[s, s + l_{i,a} \right) \end{cases}$$

When the power consumption vector of the "shiftable" appliances are obtained, total "shiftable" power consumption is given by

$$x_{i}^{t} = \sum_{a \in \mathcal{A}} x_{i,a}^{t}$$

So the total power consumption vector of "shiftable" appliances is shown as $\mathrm{x}_{i} = \left[x_{i}^{1}, \ldots, x_{i}^{t}, \ldots, x_{i}^{T} \right]$

For the initial situation, it is assumed that every household starts with "non-shiftable" predetermined profile. So the real-time load vector of user i is then updated as $\mathrm{q}_{i} = \mathrm{u}_{\mathrm{i}} + \mathrm{x}_{i} = \left[q_{i}^{1}, q_{i}^{2}, \ldots, q_{i}^{T} \right]$. So then the total consumption vector is given as $\mathrm{q}_{t} = \sum_{i=1}^{N} \mathrm{q}_{i}$ and the consumption at time slot t is $q_{t} = \sum_{i=1}^{N} u_{i}^{t} + x_{i}^{t}$.

ECS is required to schedule all appliances within the horizon $\mathcal{T}$ so then the sum of the optimal scheduled start time s and the operation duration of appliance $l_{i,a}$ has to be smaller than time horizon $\mathcal{T}$.

Given the price vector $\mathrm{p}_{t} = \left\{ p_{1}, p_{2}, \ldots, p_{T} \right\}$ for the time horizon T and the "shiftable" appliance power usage $c_{i,a}$ during the operation period, the optimal scheduled start time s^{*} is obtained by solving the following optimization.

$$\min_{s} \sum_{r=s}^{s+l_{i,a}} p_r c_{i,a}$$

subject to $s + l_{i,a} \le T$

The optimization problem can also be written as

$$\min_{s} \sum_{r=s}^{s+l_{i,a}} \left[\phi_t + e^{(q_t - \overline{q})} \right] c_{i,a}$$

subject to $s + l_{i,a} \le T$

5.2.4 Distributed Algorithm

User i has a request to turn on appliance a for the given day. Then optimal start time s^* for this appliance is calculated by solving the optimization problem: $\min_{s} \sum_{r=s}^{s+l_{i,a}} p_t c_{i,a}$ subject to $s + l_{n,a} \le T$.

Here, it is assumed that there is no "shiftable" appliance consumption for the initial position, so $\mathrm{q}_i = \mathrm{u}_\mathrm{i}$. After solving optimal start time s^* , "shiftable" appliance consumption vector $\mathrm{x}_{i,a} = \left[x_{i,a}^1, \ldots, x_{i,a}^t, \ldots, x_{i,a}^T \right]$ is created. By adding "shiftable" appliance consumption vector on predetermined "non-shiftable" appliance consumption, new total consumption vector of user i is obtained:

$\mathrm{q}_i' = \mathrm{u}_\mathrm{i} + \mathrm{x}_{i,a} = \left[q_i'^1, q_i'^2, \ldots, q_i'^T \right]$

The new total consumption vector is obtained by $\mathrm{q}_t' = \sum_{i=1}^{N} \mathrm{q}_i'$ and is sent to service provider. New price vector is computed by using new total consumption vector, new price vector is computed by $p_t' = \phi_t + e^{\mu(q_t' - \overline{q}')}$.

<u>**Algorithm 1** Executed by the service provider</u>

1: Initialization.
2: **repeat**
3: **if** receive request signal from ECS user i for app a **then**
4: Compute the initial price vector p_t using $p_t = \phi_t + e^{\mu(q_t - \overline{q})}$
6: Send p_t to ECS user $i \in N$.
7: **for all** start time s^* received **do**
8: Compute new q_t' and $\overline{q}'$
9: Compute new price vector p_t', using $p_t' = \phi_t + e^{\mu(q_t' - \overline{q}')}$
10: Send p_t' to ECS user $i \in N$.
11: **end for**
12: **end if**
12: **until** the end of the day

Algorithm 2 Executed by the ECS i

1: Initialization.
2: **if** consumer i has a request for appliance a for the given day **then**
3: Send the request signal to service provider.
4: **for all** price vector p_t received **do**
5: Solve $\min_{s} \sum_{r=s}^{s+l_{i,a}} p_t c_{i,a}$ subject to $s + l_{n,a} \leq T$ to find optimal s^*
6: Send s^* to service provider.
7: **end for**
8: **end if**

5.2.5 Simulation Results

In this section, simulation results are represented and assessed the performance of the proposed algorithms. In considered benchmark smart grid system there are $N = 25$ customer/users that subscribe to the ECS services.

Performance Comparison

The simulation results on total scheduled energy consumptions and the energy cost for a single scenario are shown in Figures 5.4 and 5.5 *with* the deployment of the ECS function in the smart meters, respectively.

For the case without ECS deployment, each appliance $a \in \mathcal{A}_n$ for each user $i \in N$ is assumed to start operation right at the beginning of the time interval and at its typical power level. For the case with ECS deployment, the timing and the power level for the operation of each household appliance is determined by algorithm 1 and 2. By comparing the results of electricity cost graphs in Figures 4.5 and 5.2, it can be concluded that when the ECS functions are *not* used/implemented the energy cost is 30.145€. At the same time, when the ECS feature is enabled, the energy cost reduces to 21.070€ (i.e., 30.11% less).

In fact, in the latter case, there is a more evenly distributed load across different hours of the day. Note that each user consumes the same amount of energy in the two cases, but it simply schedules its consumption more cost efficiently in the case that the ECS units are used.

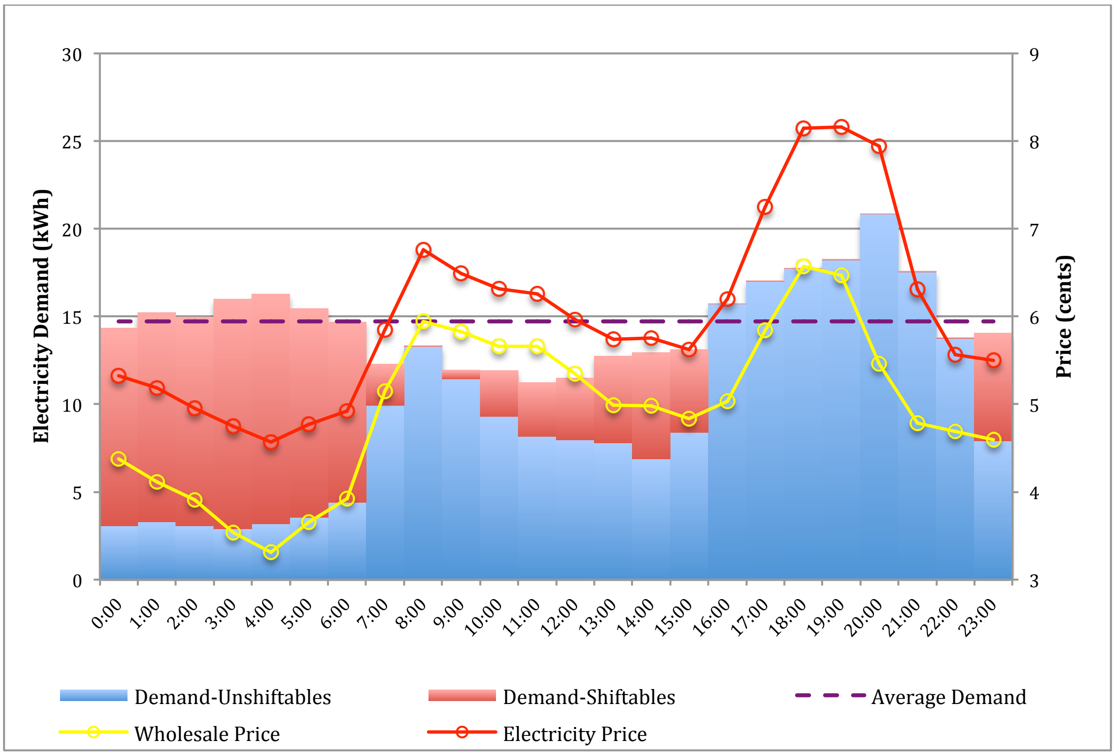


Figure 5.4 Hourly shiftable and non-shiftable electricity demand and electricity prices with ECS deployment

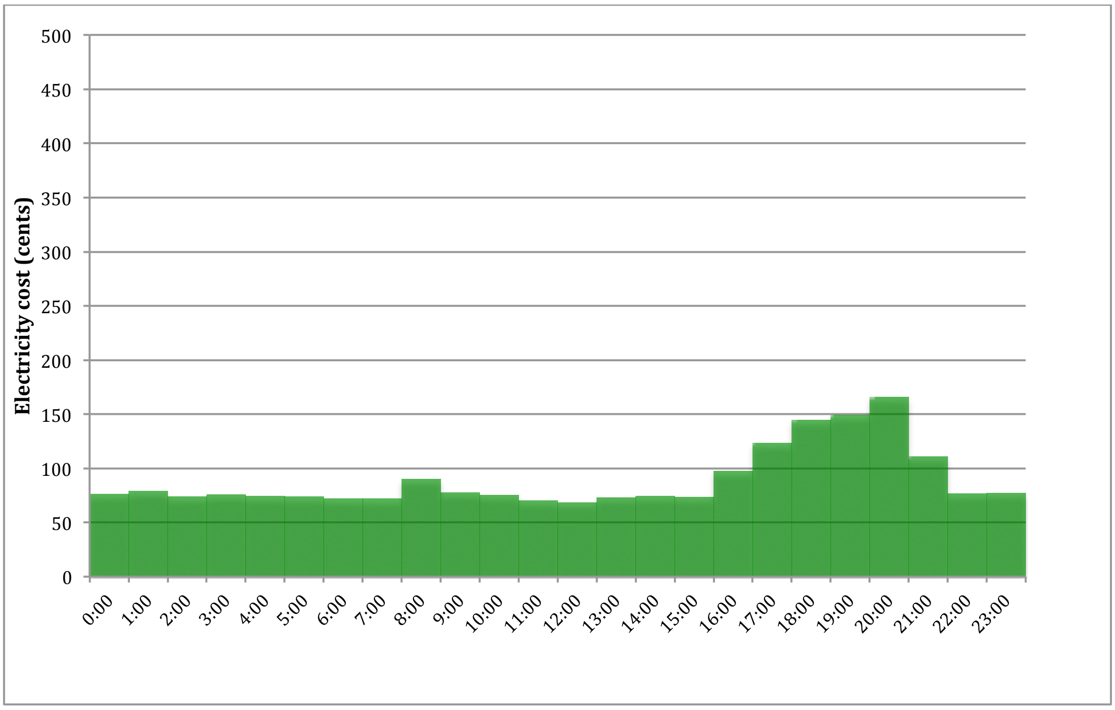


Figure 5.5 Hourly energy cost of 25 houses with ECS deployment

User Payment

While the proposed distributed DSM strategy leads to less total energy cost, it is also beneficial for each individual end user. To see this, the daily payments for all users are shown in Figure 5.6. Here, the simulation setting is the same. We can see that all users would pay significantly less to the utility company when the

ECS is enabled in the smart meter. Therefore, the users would be willing to participate in the proposed automatic demand-side management system.

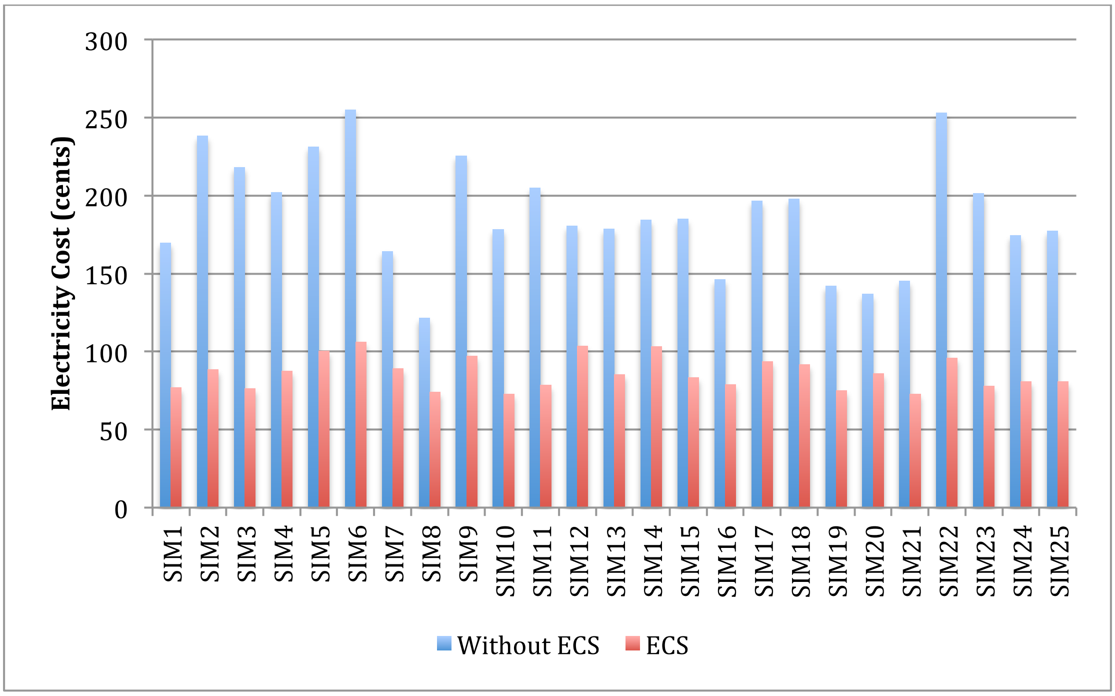


Figure 5.6 Electricity cost of each household with/without ECS deployment

Impact of Amount of Shiftable Load

For the simulation scenarios so far, we have assumed that around %33.3 of the residential load is shiftable while the other %66.6 is not shiftable. Clearly, the ECS units are expected to have a more significant impact if more appliances have shiftable operation.

6 Investment Performance of Photovoltaic Solar Panels

It is proven in Chapter 5 that proposed retail electricity pricing model, proposed in Chapter 4, is advantageous for the household consumers who are willing schedule their appliances with a game theoretical framework. In this chapter, PV solar panels investment performance of the household consumers is compared in two cases; conventional fixed electricity pricing scheme and real-time pricing with ECS deployment.

6.1 Subsidies for Photovoltaic Solar Panels in The Netherlands

6.1.1 Solar Subsidy

From Monday, July 2, 2012, the scheme is opened and individuals can apply for grants for solar installations (solar PV). Agentschap NL implements the scheme in the Ministry of Economic Affairs, Agriculture and Innovation.

For a solar PV installation with a minimum capacity of 0.601 kWp (kilowatt peak) to 3.5 kWp subsidy is 15% of actual purchase costs. The grant for a solar plant with a capacity greater than 3.5 kWp (kilowatt peak) was calculated as follows: the outcome of 15% of actual cost is multiplied by 3.5 and divided by the power kilowatt peak. The investor can be subsidised maximum of 650 euro in all cases.

6.1.2 Feed-in tariff

Net metering law provides up to 5,000 kWh of surplus electricity. Households, who consume less than 5,000 kWh of electricity, will receive the feed-in tariff as equal to the delivery rate including energy tax and VAT.

6.2 Method of Payback Time of The Investment

6.2.1 Cash Flow of PV Solar Panel Investment

The especial features of PV systems together with the economic incentives taken into account in the analysis suggest that any cash flow involved in it should make a contribution to one of the following two concepts:

a. The annualised cost of the system from the user standpoint (PV_{ann}); this concept is opposed to the life-cycle cost of the system from the grid standpoint, which considers costs that exlude tax exemptions, buy-down or grant policies, low or interest-free loans, etc.
b. The annual cash inflows from the system.

Annualised cost of the system from the user standpoint

Parameter PV_{ann} is the sum of the annualised of the initial user investment on the PV solar panels (PMT_{ann}) plus the annual operation and maintenance cost (PV_{aom}):

$$PV_{ann} = PMT_{ann} + PV_{aom}$$

If PV_{in} is the initial investment on the PV solar panels while PV_{bd} is stated as the initial buy-down subsidy, $PV_{in} - PV_{bd}$ is to be paid by the owner. However, if this amount is borrowed at an annual loan interest i, total payments of each year (PMT_{ann}) during the loan period (N, in years) can be set equal so that [49]:

$$PMT_{ann} = (PV_{in} - PV_{bd})i\left[\frac{(1+i)^N}{(1+i)^N - 1}\right]$$

where PV_{aom} is the annual operation and maintenance cost, according to [73] $PV_{aom} = 0.01PV_{in}$.

The annual cash inflows from the system

The annual cash inflows from the system ($CF(N)$) are related to government generation-based incentives. The most general case would assume that part of the annual PV yield (E_{PV}, in kWh) is sold at a given price (p_s, in €/kWh), which is usually above the market level. N (years) is the serviceable life of the system.

$$CF(N) = p_s E_{PV}$$

6.2.2 Payback time

The payback time of an investment project (more properly, the discounted payback time, $DPBT$) is the required number of years for the annualized worth of the inflows to equal the annualised worth of the outflows. Evidently, profitability means that the discounted payback time should not exceed the serviceable life of the system ($DPBT < N$). Although easily understandable and straightforward, this parameter does not consider the cash flows that are produced after the DPBT. Hence, it may hide sound financial opportunities for those deciding to invest on a PV system [14].

6.3 Results

Results are given under two different conditions, current situation and proposed situation. In current situation, payback period of PV solar panels are calculated in case of no electricity consumption scheduler (ECS); in proposed situation, pay period of PV solar panels are calculated in case of ECS.

There are five different PV solar systems offered by NUON Electricity Company in the Netherlands. Three out of these five PV solar systems were selected as possible investment options for the majority of household consumers.

Table 6.1 PV solar panel projects offered by NUON[3]

	Package A	Package B	Package C
Peak generation (kWp)	1080	1880	2820
Total area of panels (m²)	7.9	13.2	19.8
Generation per year (kWh)	920	1600	2400
Cost including the installation (€)	3000	4600	6200

[3] http://www.nuon.nl/energie-besparen/zonne-energie/zonnepanelen/prijzen-en-opbrengst.jsp

Payback Time of PV Systems in Current and Proposed Situation
It is assumed that all these three packages are applied with a bank loan with 4% annual interest rate. Subsidies summarized in Section 6.1, are added on the capital cost of PV solar panels and the equivalent annual capital cost is obtained by the methodology given in Section 6.2.1.

In current situation, retail electricity prices are fixed; household consumers do not have real-time electricity price option. As a matter of fact, household consumers do not schedule their electricity consumption. In this case, the economical benefits of ECS will not be taken into consideration when the payback period is calculated.

Table 6.2 Payback time of PV Systems in Current Situation

	Package A	**Package B**	**Package C**
Expected payback time	21.05	17.32	15.63
Annualised Capital Cost of PV systems			
Cost of capital	0.04	0.04	0.04
Capital Cost of PV (€)	3000	4600	6200
Subsidy on PV investment (€)	450	650	650
Initial Investment (€)	2550	3950	5550
Equivalent Annual capital cost (€/year)	181.50	320.50	484.50
Annual Cost of OM (€/year)	25.50	39.50	55.50
Total annual cost (€/year)	**207**	**360**	**540**
Cash inflow			
Electricity sold (€/kWh)	920	1600	2400
Feed-in tariff (€/kWh)	0.225	0.225	0.225
Annual cash inflow from PV (€/year)	207	360	540
Profit from Scheduler (€/year)	0	0	0
Total annual cash inflow	**207**	**360**	**540**

In the proposed situation, household consumers are exposed to real-time electricity pricing scheme. So then household consumers are using electricity consumption scheduler at their homes to benefit from real-time pricing scheme as much as possible. On the Table 6.3, profit from the scheduler is given; this is derived from the results of Chapter 5.

When the ECS functions are *not* used/implemented the energy cost is 30.145€ for 25 households. At the same time, when the ECS feature is enabled, the energy cost reduces to 21.070€ (i.e., 30.11% less) for 25 households. If it is assumed that this cost reduction is the average cost reduction in a year, it makes 125.34 €/year save for one household. This assumption can be improved further by running the simulations for every two weeks of a month and then averaging the profits, this assumption will be discussed further in the next chapter.

Table 6.3 Payback time of PV Systems in Proposed Situation

	Package A	Package B	Package C
Expected payback time	10.30	11.16	11.54
Annualised Capital Cost of PV systems			
Cost of capital	0.04	0.04	0.04
Capital Cost of PV (€)	3000	4600	6200
Subsidy on PV investment (€)	450	650	650
Initial Investment (€)	2550	3950	5550
Equivalent Annual capital cost (€/year)	306.84	445.84	609.84
Annual Cost of OM (€/year)	25.50	39.50	55.50
Total annual cost (€/year)	332.34	485.34	665.34
Cash inflow			
Electricity sold (€/kWh)	920	1600	2400
Feed-in tariff (€/kWh)	0.225	0.225	0.225
Annual cash inflow from PV (€/year)	207	360	540
Profit from Scheduler (€/year)	125.34	125.34	125.34
Total annual cash inflow	332.34	485.34	665.34

PV solar panels have 25 years of lifetime. In the current situation, PV systems payback their costs when they are already older than half of their life. In the proposed situation, there is a visible improvement in payback time. After 10-12 years, the investment pays back and later the PV investor enjoys the profits.

7 Conclusions and Future Work

7.1 Conclusions

Main goal of this research is to reduce the electricity cost of household consumers while maintaining the same level of comfort. To achieve this goal, real-time electricity pricing model with game theoretical electricity scheduling is suggested for the household consumers.

The following research question was answered during this research: *"How can household consumers benefit economically from time-varying pricing schemes with game-theoretic electricity consumption scheduling?".* To answer this research question, the sub-question "How can electricity-pricing incentive be built to motivate household consumers to schedule their "shiftable" appliances?" is given and a model is proposed on Chapter 4. Later, the sub-question "How can a game theoretic framework be used for electricity scheduling to minimise electricity costs of household consumers?" is researched and the simulations in Chapter 5 give the numerical results. Moreover sub-question "How are investment of photovoltaic solar panels economically feasible in time varying price incentive with electricity scheduling game situation?" is answered by comparing the payback periods of conventional fixed pricing case and the proposed ECS model.

7.1.1 Electricity Pricing Model

Electricity pricing scheme for this thesis is proposed to be real-time pricing. Real-time pricing scheme can be applied in different ways; the retailer can give the next hour-prices either an hour before or a day before. In this thesis, it is assumed that retailer declares prices a day before. Electricity pricing model proposed by this thesis does not exist in real life, so the results for the benefit of deploying ECS can change from one electricity-pricing model to another.

Modelling Price Gap

In the proposed electricity-pricing model, price gap plays an important role. Since this gap is designed to motivate household consumers to schedule their "shiftable" appliances, it is important to recall the formula and test it with changing design factor values.

$$\rho_t = e^{\mu(q_t - q_{average})}$$

Price gap is given by the formula below. This gap could have been designed in many other ways; but in this thesis, exponential function is proposed. Different designs would have resulted different outcomes of simulations.

Design Factor

Design factor μ plays an important role in calculating the price gap. Changing design factor would change the electricity cost of households in both deployment of ECS and no deployment of ECS.

There are three important conclusions, which can be drawn from the Figure 7.1:

1 The proposed electricity-pricing model is not advantageous for the household consumers when design factor is 0.075 and higher.
2 Electricity cost of households are not affected drastically by the design factor when the household consumers are deployed with ECS, on the other side electricity cost of households are increasing drastically by the design factor when the household consumers are not deployed with ECS.
3 Overall, deployment of ECS with real-time pricing is always advantageous when compared to the conventional fixed pricing scheme.

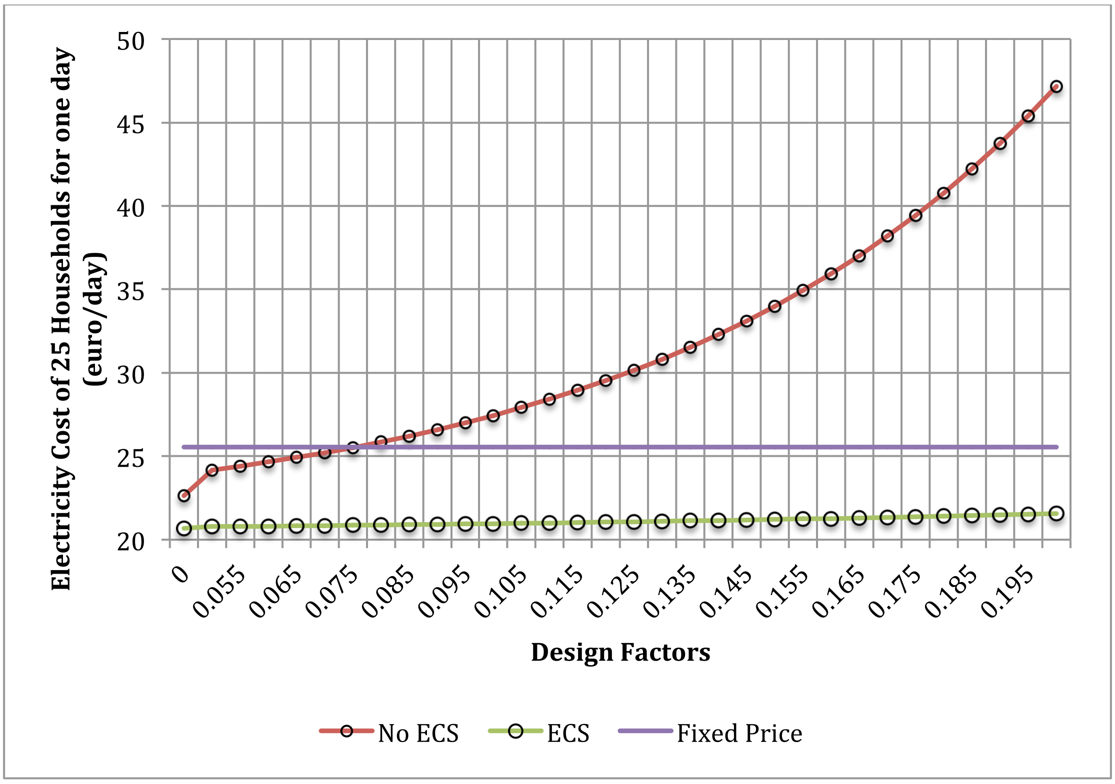


Figure 7.1 Effect of design factor in real-time pricing with/without deployment of ECS and fixed pricing schemes

7.1.2 Algorithm of Electricity Scheduler

Algorithm of electricity consumption scheduler is starting with a signal from the "shiftable" appliance of household consumer, which is a random case. When the simulations were run, it is assumed that every household is using washing machine, dishwasher and cloth dryer in the same day and running them in a sequential order.

This assumption causes results to be more unrealistic. For example, in the day of simulation of 25 households, it is assumed that the cloth dryer runs first in every household and then the dishwashers and then the cloth dryers, which would not be the case in the real life.

7.1.3 Results

Electricity Cost Reduction

In the case where household consumers do use real time prices, but do not deploy ECS, it is shown that the proposed retail electricity-pricing model is very volatile (red line on the Figure 7.2). This is causing electricity costs for every hour to be volatile too and the sum of the electricity costs shows that when the ECS functions are *not* used/implemented the electricity cost is 30.145€ for 25 households.

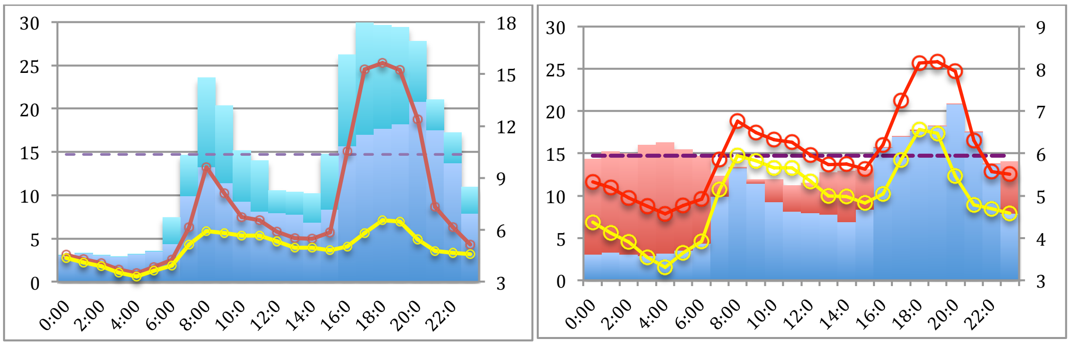


Figure 7.2 Hourly shiftable and unshiftable electricity demand and electricity prices with and without ECS deployment

When the proposed model of real-time pricing with game theoretical electricity consumption scheduling is applied, electricity cost of 25 households drops to 21.070€, which is 30.11% less compared to the conventional fixed pricing case. So it is concluded that the proposed real-time electricity pricing with electricity consumption scheduling model help household consumers to reduce their electricity costs.

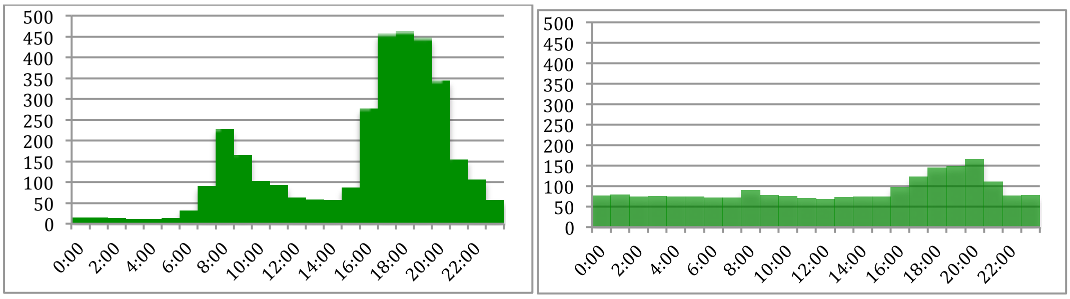


Figure 7.3 Hourly electricity cost of households with and without ECS deployment

If the one-day simulation result is generalized for whole year, one household profits 125.34 € in one year.

Investment Performance of PV solar Panels

Investment performance is observed by comparing the payback periods of PV solar panels for both cases; with and without ECS deployment. It is shown that the payback period decreases drastically when the proposed real-time pricing with ECS scheduling is applied.

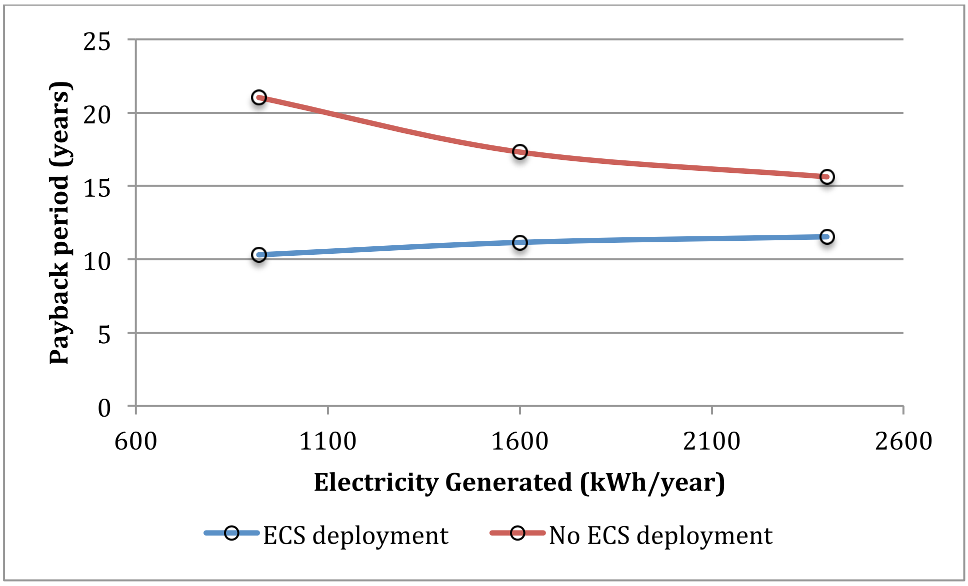


Figure 7.4 Payback periods of three PV solar system packages

7.2 Future Works

In the future works, the following subjects can be improved:

- Electricity demand profile generation can be applied better for a specific country.
- Different real-time pricing models can be suggested and compared. If the research is done with the sponsorship of an electricity retail company, their pricing model can be applied to see more realistic results to compare the fixed pricing scheme with real-time pricing scheme.
- Simulation program of game theoretical model can be improved; so then electricity usage requests of the consumers are also randomized.
- Payback periods of more micro-generation applications, such as micro combined heat and power (micro CHP) and heat pumps can be evaluated, moreover these applications can be also simulated for better results.
- Next-hour electricity forecasting can be analysed from the risk management point of view and risk management of the whole proposed model can be given.

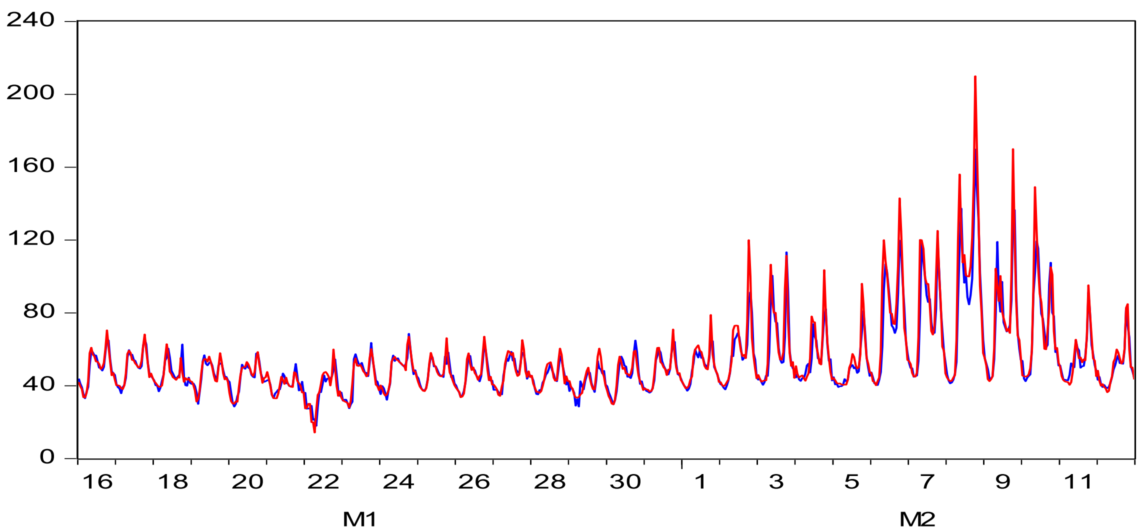
Appendix A

Daily Mean Absolute Error and Mean Weekly Error

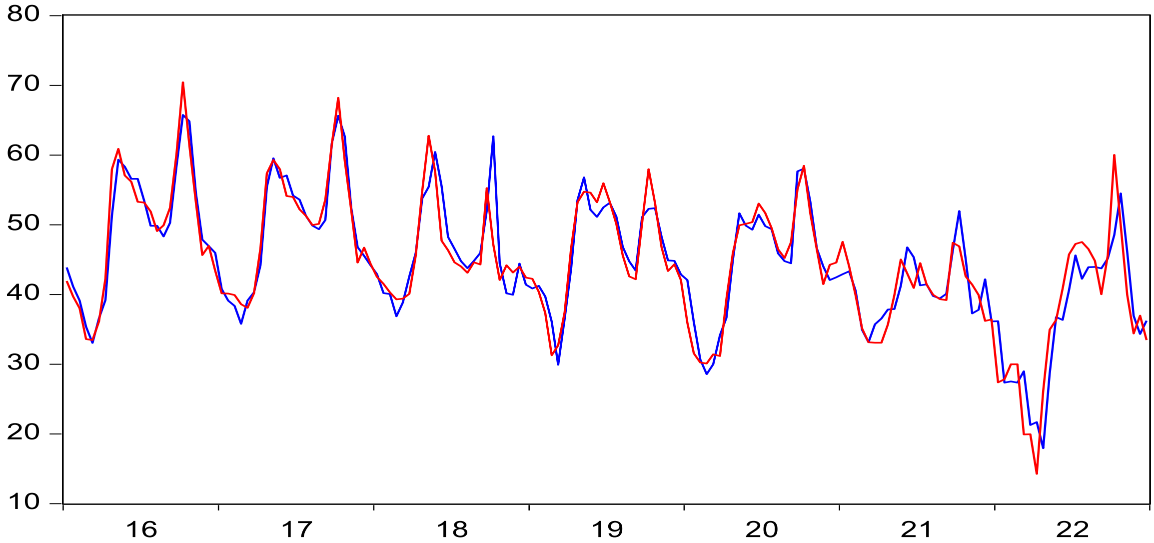
Forecasted period	APX daily	MAE daily	MDE
1/16/12	49.509	1.926	0.0389
1/17/12	50.018	1.313	0.0263
1/18/12	45.696	2.658	0.0582
1/19/12	46.298	1.828	0.0395
1/20/12	44.222	1.795	0.0406
1/21/12	40.233	2.245	0.0558
1/22/12	36.657	4.229	0.1154
1/23/12	44.060	1.942	0.0441
1/24/12	48.916	1.599	0.0327
1/25/12	46.720	1.886	0.0404
1/26/12	46.221	1.743	0.0377
1/27/12	48.459	2.406	0.0496
1/28/12	45.385	1.916	0.0422
1/29/12	42.541	2.992	0.0703
1/30/12	44.415	2.579	0.0581
1/31/12	48.733	1.928	0.0396
2/1/12	51.210	2.413	0.0471
2/2/12	60.041	5.257	0.0876
2/3/12	63.689	6.343	0.0996
2/4/12	57.432	4.852	0.0845
2/5/12	51.720	3.048	0.0589
2/6/12	78.947	7.897	0.1000
2/7/12	78.106	5.949	0.0762
2/8/12	98.983	12.200	0.1233
2/9/12	76.487	7.782	0.1017
2/10/12	74.249	6.902	0.0930
2/11/12	54.653	2.885	0.0528
2/12/12	51.137	2.463	0.0482

Forecast Results

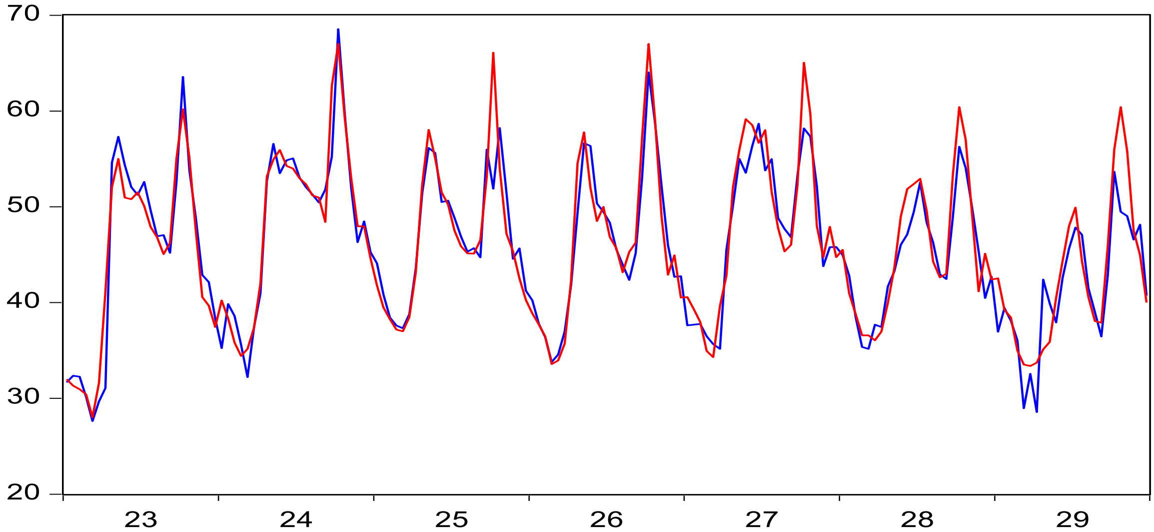
Below are the graphs of predicted and real APX-Endex prices, red is the real price, blue is the predicted price.



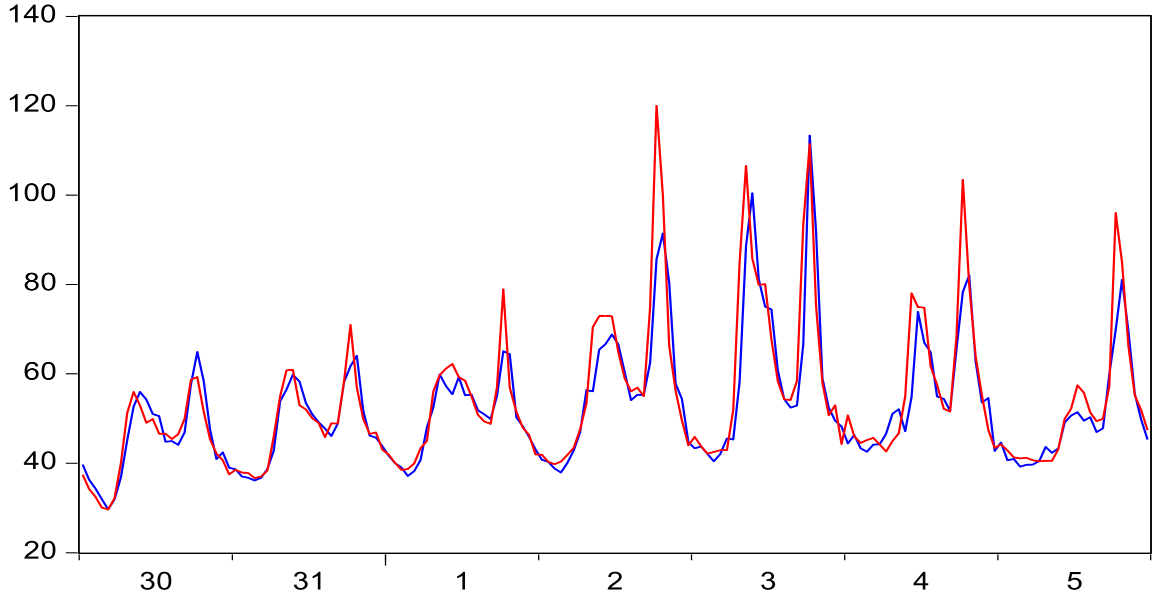
January 16 – February 12 2012 Results



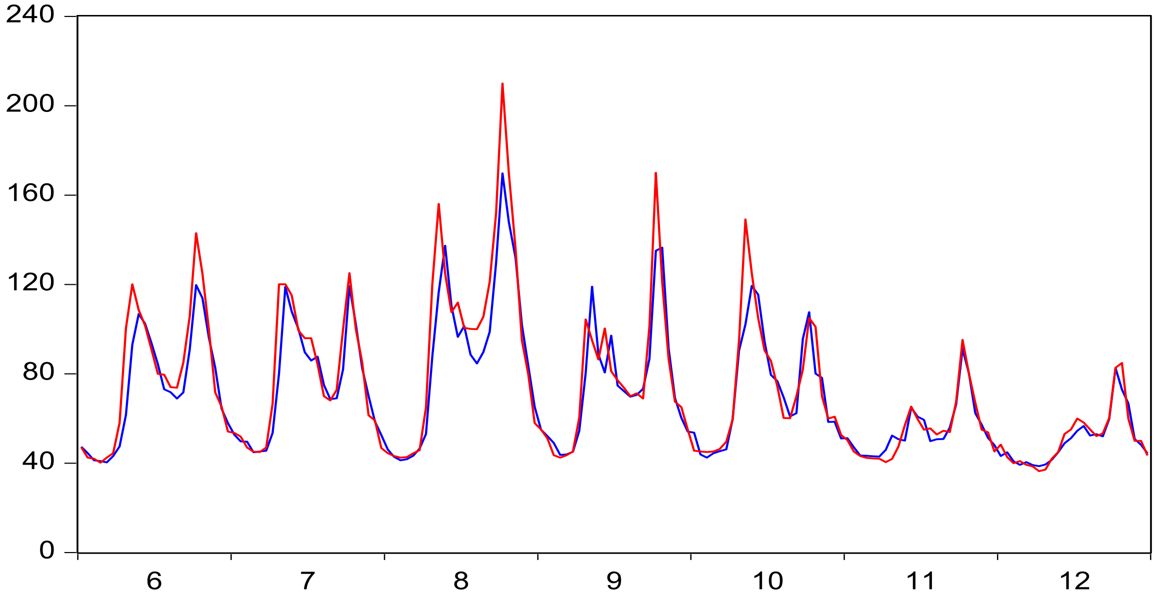
1 January 16-22 Results



January 23-29 Results



January 30 – February 5 Results



2 February 6 – 12 Results

Appendix B

Hours	APX - Wholesale Price (cents/kWh)	Price Gap	Retail Electricity Price (cents/kWh)
0:00	4.377	0.235	4.612
1:00	4.111	0.242	4.352
2:00	3.910	0.235	4.145
3:00	3.540	0.230	3.769
4:00	3.308	0.238	3.546
5:00	3.656	0.249	3.905
6:00	3.927	0.404	4.331
7:00	5.148	0.994	6.142
8:00	5.941	3.026	8.967
9:00	5.829	2.023	7.852
10:00	5.656	1.063	6.719
11:00	5.658	0.921	6.580
12:00	5.347	0.598	5.945
13:00	4.991	0.585	5.576
14:00	4.984	0.572	5.556
15:00	4.834	1.006	5.840
16:00	5.034	4.236	9.271
17:00	5.838	6.700	12.538
18:00	6.572	6.472	13.045
19:00	6.472	6.290	12.761
20:00	5.461	5.155	10.617
21:00	4.782	2.213	6.996
22:00	4.688	1.379	6.067
23:00	4.593	0.626	5.219

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