Investigation of Energy Demand Modeling and Management for Local Communities

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Investigation of the Electricity demand modeling and management including consumption behaviour, dynamic tariffs, and use of renewable energy

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Keywords

Electricity Load Profile, Demand Side Management, Energy Consumption, Electrical Appliances, Electricity Tariff, Demand Response, Sustainability.

Abstract

Various forecasting tools, based on historical data, exist for planners of national networks that are very effective in planning national interventions to ensure energy security, and meet carbon obligations over the long term. However, at a local community level, where energy demand patterns may significantly differ from the national picture, planners would be unable to justify local and more appropriate intervention due to the lack of appropriate planning tools.

In this research, a new methodology is presented that initially creates a virtual community of households in a small community based on a survey of a similar community, and then predicts the energy behaviour of each household, and hence of the community. It is based on a combination of the statistical data, and a questionnaire survey. The methodology therefore enables realistic predictions and can help local planners decide on measures such as embedding renewable energy and demand management.

Using the methodology developed, a study has been carried out in order to understand the patterns of electricity consumption within UK households. The methodology developed in this study has been used to investigate the incentives currently available to consumers to see if it would be possible to shift some of the load from peak hours. Furthermore, the possibility of using renewable energy (RE) at community level is also studied and the results presented. Real time pricing information was identified as a barrier to understanding the effectiveness of various incentives and interventions. A new pricing criteria has therefore been developed to help developers and planners of local communities to understand the cost of intervention. Conclusions have been drawn from the work. Finally, suggestions for future work have been presented.

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Acronyms

AMI	Advanced Metering Infrastructure
BESS	Battery Energy Storage System
CSV	Comma Separated Values
CPP	Critical Peak Pricing
CDF	Cumulative Distribution Functions
DR	Demand Response
DSM	Demand Side Management
DEFRA	Department for Environment Food and rural affairs
DECC	Department of Energy and Climate Change
DHW	Domestic Hot Water
ECUK	Energy Consumption in the UK
ERP	Energy Reduction Program
FIT	Feed In Tariff
GDP	Gross domestic product
GHS	Green House Gas
HVAC	Heating, Ventilation and Air-Conditioning
HH	Household
IRP	Integrated Resource Planning
LMP	Load Management Program

MPAN	Meter Point Administration Number
OECD	OECD countries
ONS	Office for National Statistics
PBP	Payback Period
PV	Photovoltaics
RTP	Real Time Pricing
RE	Renewable Energy
RETs	Renewable Energy Technologies
SBP	System Buy Price
SMLP	Simple Method Load Profile
SSP	System Sell Price
SM	Statistical methods
SSM	Supply Side Management
TOU	Time of Use

Chapter 1

Introduction

1.1 Background

Estimating load profile data is vital for planning electricity distribution networks and optimal generation capacity. Energy planners require this data in order to design and operate an optimal energy system from an economic, environmental and technical perspective. Electricity demand models are often used to forecast the demand at the national level.

Various forecasting tools, based on historical data, exist for planners of national networks that are very effective in planning national interventions to ensure energy security, and meet carbon obligations over the long term. However, at a local community level, where energy demand patterns may significantly differ from the national picture, planners would be unable to justify local and more appropriate intervention due to the lack of appropriate planning tools.

The most typical application of electricity demand models is the short and long term forecasting of future use [1]. Intuitively, direct measurements look like being the best, observable way to collect quantitative information about residential energy consumption. Indeed, measurements of total residential electricity use in individual households can be obtained quite easily, but to determine the proportions of different end-uses, specific measurement devices have to be installed. Therefore, most quantitative studies of household electricity look at total electricity demand. However, following the growth of rules in order to increase energy efficiency there is better attention to detail regarding what people essentially use electricity for. This approach is not cost effective due to the equipment and high processing costs [2]. Moreover, a significant amount of time would be required to build up such a system. Load modelling could be a viable alternative to this approach.

Load balancing is also a major concern for several countries, particularly where the demand is close to the available generation capacity. This is represented in the deregulated market by higher pricing during peak periods. Continuous growth in peak load raises the possibility of power failure, and raises the marginal cost of supply. The lack of domestic consumers' awareness of the dramatic rises occurring as a result of simultaneous high energy use is one of the key reasons contributing to increases in load peaks.

In the UK the domestic sector accounts for about one third of the total electricity use [3]. It contributes the largest peak demand, particularly in the winter season, which has consequences for the power infrastructures. This ratio is expected to increase considerably in the coming years.

Under competitive electricity market conditions, if reasonable financial incentives are provided to consumers, they could be encouraged to modify the style of their consumption in response of financial incentives [4]. Consequently we can achieve the objective of making the load more level and recover the stability and efficiency of the power system.

As a result of fossil fuels becoming ever more expensive, renewable energy power use has been increasing rapidly in the UK over recent years [5]. Even though the availability of hydroelectric power is practically predictable and controllable, renewable power (solar and wind) are only available when the weather permits. It is therefore problematic to match supply to demand. A way to incorporate renewable energy resources into the system is to combine them with storage elements to plug the supply gap when the renewables are not available, or to do peak load shaving [6].

The renewable energy generated in a local community rather than on a national scale can be considered as one of the key solutions to the current global challenges but it is also vital for renewable energy projects to be developed by or with the close involvement of local people, and to ensure that a local community experiences benefits within relatively short time periods. Instead of producing a large amount of energy in a few places and using very inefficient long distance transmission cables to deliver it, it is possible to produce smaller amounts of power in many places from the most appropriate renewable sources. Energy can then be fed back into the distribution network, or potentially consumed locally via localized distribution networks.

Future smart grids with disperse renewable resources provide a wide range of new features including smart metering, demand side management and integration of storage elements. One of the drivers of smart grid deployment is the optimal integration of embedded generation, as well as of energy storage systems and demand side management (DSM) systems [7]. Smart grids will give customers the ability to control energy consumption, using demand response. Such factors as peak shifting and overall conservation will impact on a demand response system.

With the developing electricity market, storage elements, smart grids and the drive for lower carbon generation technologies there is the opportunity to support consumer participation in the electricity market in future, especially if they have energy production of their own. So, the energy market is becoming more attractive and competitive. Therefore, local energy solutions should be introduced to ensure an efficient use of various energy resources and infrastructure.

1.2 Research objectives

The objectives of this thesis are:

- To develop a methodology that enables the prediction of realistic electricity load profiles at half hourly intervals for local residential communities in order to help local planners decide on measures such as embedding renewable energy and demand management.
- To investigate incentives available to consumers that help in load shaving. This includes the use of electricity storage elements on a local residential community, rather than national scale.
- To investigate the potential and optimization of residential tariffs schemes that could influence consumer behaviour and how these tariffs can be used to achieve cost effective peak demand reduction via load shifting.
- To increase knowledge and understanding of the patterns of electricity consumption and load curves within UK households (which is of use to electricity producers and distributers) in order to study measures that could be used to reduce energy consumption.
- To investigate the use of renewable energy generated at local residential community level.
- Investigate measures to help planners understand the cost of intervention in the domestic energy sector.

1.3 Thesis organization

The thesis is divided into eight chapters starting with the introduction. In chapter 2, a literature review is presented, discussing the energy trends in the UK domestic sector. A review of the various techniques that have been developed through the years for modelling residential sector energy consumption is provided. Factors affecting electricity demand and consumers' behaviour, and occupancy patterns are explained.

Chapter 3 describes two cases to demonstrate the use of the traditional load profile tools. The first case focuses on the use of the regression analysis technique to develop a model for household electricity consumption on a monthly basis; the model considers the results of previous study and monthly consumption derived from electricity bills as input data. This is followed by the second case which describes and investigates the analysis of electric energy data obtained from a monitoring study of the electricity consumption of a single-family household with two adults and children. The results are presented and discussed.

In chapter 4, a methodology for generating realistic load profiles at a residential community level and its key data sources are presented. The results are presented and discussed.

Chapter 5 presents and discusses the investigation of economy7 tariffs as an incentive to generate demand response and shows its impact on consumer behaviour in UK domestic buildings using the results presented in chapter 4. This is followed by an investigation of an optimization of residential tariffs scheme which could influence consumers' behaviour to achieve cost effective peak demand reduction via load shifting.

Chapter 6 contains an evaluation and investigation of the impact of using renewable energy on local communities based on the methodology presented in chapter 4. This is followed by an investigation of optimisation of residential tariffs schemes that could influence consumers' behaviour. The results are presented and discussed.

Chapter 7 demonstrates pricing criteria to help developers and planners of local communities to understand the cost of intervention in order to evaluate where the load is when the prices are high. The results are presented and discussed.

Finally, in chapter 8 a summary and conclusion of the thesis are presented, as well as suggestions for future work.

Chapter 2

Literature Review

2.1 Background

Adequate information on the electricity consumption pattern of consumers is necessary as a basis for assessing the influence of any initiative to reduce overall electricity use and determine the amount of overall reduction which occurs during different times of the day. With this information, utilities would be able to develop trading and marketing strategies and have the ability to design specific tariff choices for the various types of consumers. This information could also be used to better address the operation of the distribution infrastructure, its future enhancement, and for integrated system planning by considering the load management alternatives that can be used to effectively meet system peak demand.

The demand characteristic is the most important factor for analyzing consumers' information. Load research has been widely used in different utilities in many countries to work out the load characteristics of consumers. Information on the consumers' consumption patterns can be gathered through the use of the daily load profile.

In this chapter, energy trends in the UK domestic sector are presented, and the various modelling techniques that have been developed through the years for modelling residential sector energy consumption are reviewed.

2.2 Literature Review

Over the years various studies have been conducted on the topic of residential electricity demand. Due to the wide range of topics, this literature review has been arranged so that key reference papers are presented.

2.2.1 Energy Trends in the UK Domestic Sector

In the UK, there are approximately 26 million houses, and the number of households in the UK increased by 17 percent between 1990 and 2010 [8-10]. In 2010, final UK electricity consumption was 328 TWh, where the domestic energy use accounted for about 36 percent% (119 TWh) of total UK final energy consumption [9]. Figure 2.1 below breaks this down by key economic sector.

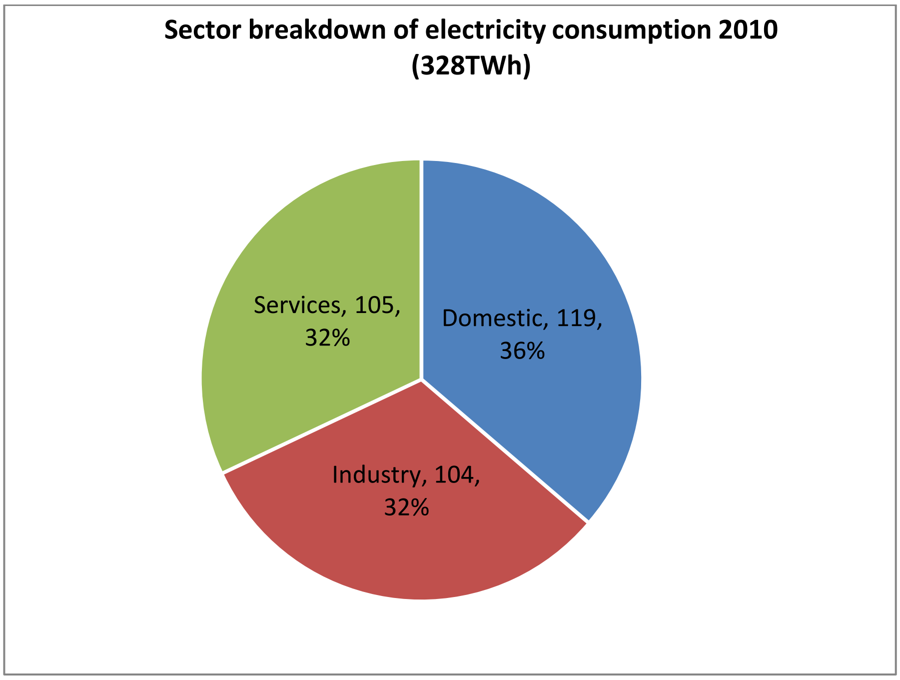

Figure 2.1 Sector breakdown of electricity consumption in 2010 [9]

The fuel mix for domestic energy consumption has significantly changed since 1970 when 39 percent of consumption was coal, 24 percent natural gas and 18 percent electricity; this changed to 8 percent coal, 63 percent gas and 18 percent electricity in 1990; and to 1 percent coal, 69 percent natural gas and 21 percent electricity in 2010, as shown in figure 2.2. This means that residential use of electricity has grown by 16.7 percent from 1990 to 2010 [9]. This indicates that residential electricity use is a significant portion of the total domestic energy use. It contributes to the largest peak demand, particularly in the winter season, which has consequences for the power infrastructure [14].

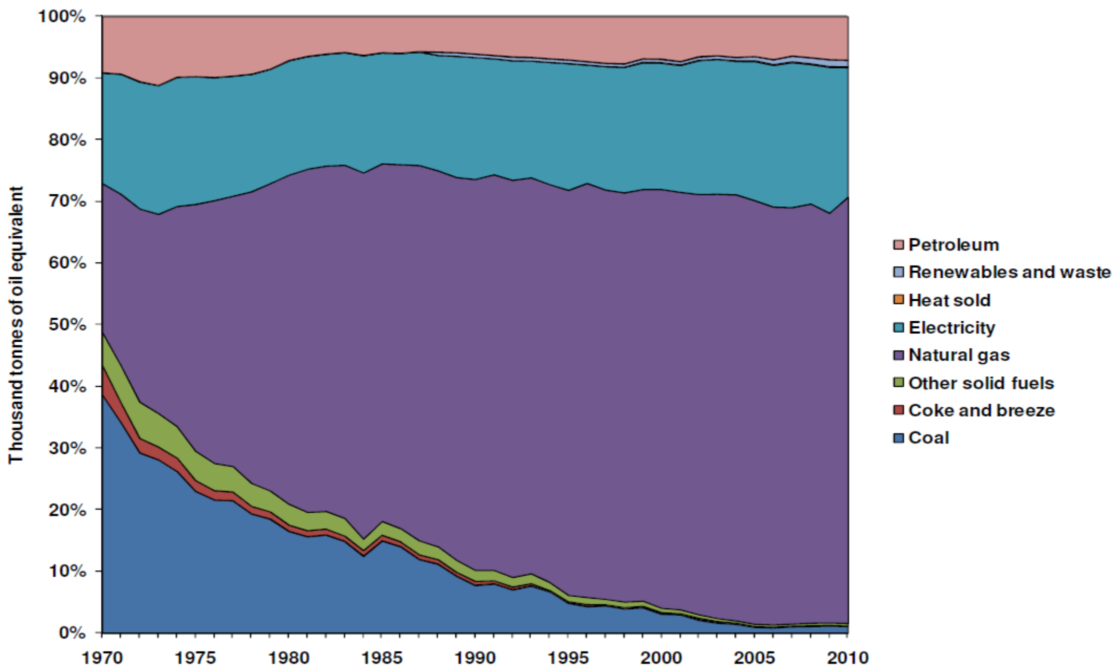

Figure 2.2 Domestic energy consumption by fuel, UK, 1970 to 2010 [9]

The UK Government's Climate Change Bill in 2007 sets a legally binding target of a 60% reduction in national CO_2 emissions by 2050 compared to 1990 levels [11]. In the domestic sector emissions have increased by 2% since 1990 despite non electricity consumption in the domestic sector increasing by 9.5% over the same period. The reason for this is considered to be the increase in the number of households, with reduced average energy consumption per household. This evidence suggests that changing household energy behaviour and reducing the use of resources by everyday practices will play a large part in reducing our national energy consumption and CO_2 emissions if the UK is to meet emissions reduction targets. Energy consumption per household has increased by 1 percent and energy consumption per person has increased by 9 percent in 1990 as shown in Figure 2.3.

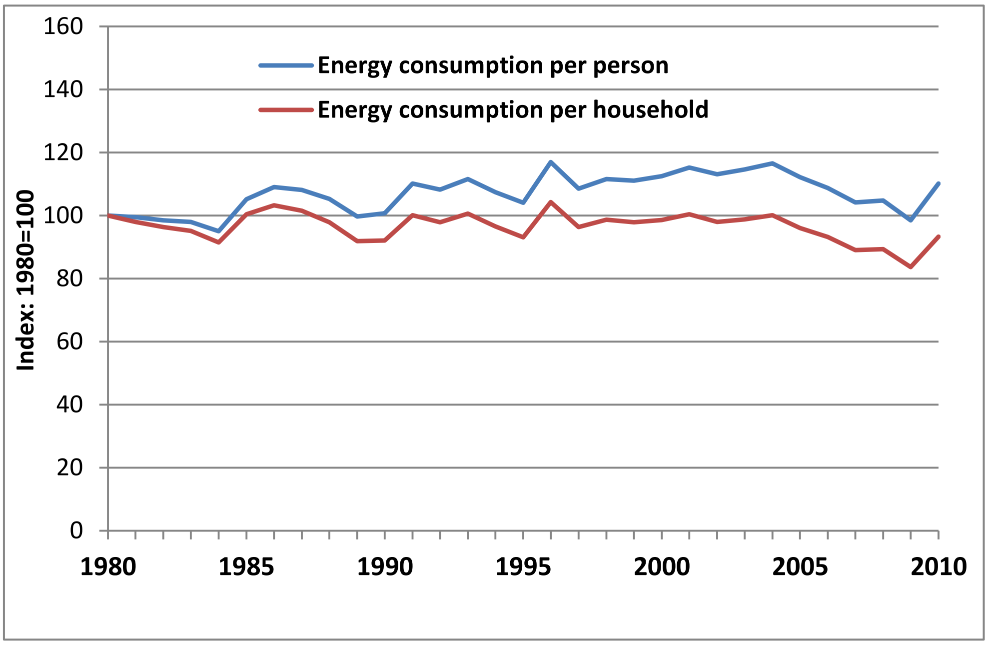

Figure 2.3 Domestic energy consumption per person [9]

Figure 2.4 below is an estimation of UK household electricity demand load by domestic appliance, for the main appliance categories: (i) lighting; (ii) cooking appliances; (iii) cold appliances (iv) wet appliances; (v) brown appliances; (vi) miscellaneous appliances [13].

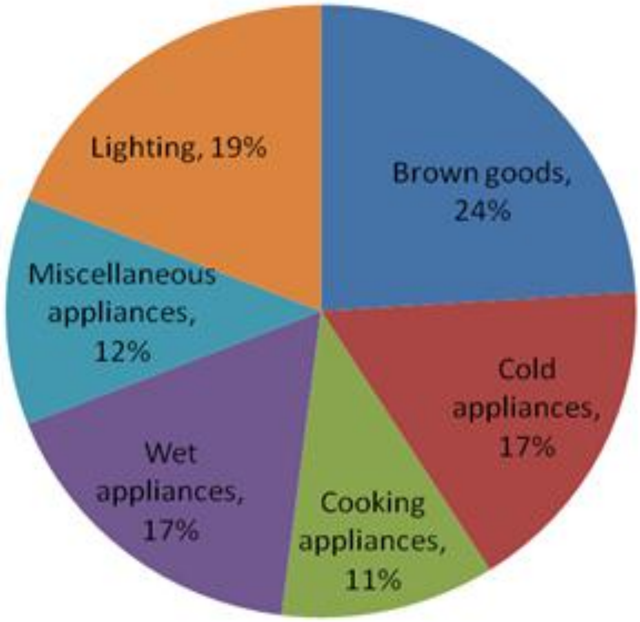

Figure 2.4 Electricity consumption by domestic appliance

According to the UK Department of Energy and Climate Change (DECC) the average domestic consumption per Meter Point Administration Number (MPAN) in 2008 was 4,202 kWh.

2.2.2 Overview of Techniques to Model Energy Consumption

This section aims to give a brief description of the various modelling techniques used for modeling residential sector energy consumption.

Domestic energy demand models might focus on a building, city, region, or nation. The electricity demand models are often applied to forecast the demand at the utility level. The data that electric utilities usually have on residential electricity use do not include much information on its nature. The data is usually the total consumption of several households without awareness of the actions in individual households. The variation of electricity use relating to an individual household remains unseen, as does the partition of use between different categories of household appliances. Alternatively detailed information can be produced with simulation models. The level of detail of input parameters is a function of data availability, model purpose, and assumptions. Increased detail allows for more wide ranging analysis of particulars, even though precise assumptions might considerably simplify the modelling procedure and provide appropriate results.

The various modelling techniques for residential energy use can be mainly classified into two approaches: top down (econometric) and bottom up (engineering). Each technique relies on different levels of input information, different calculation or simulation techniques, and provides results with different applicability. The terminology is with reference to the hierarchal position of data inputs within the domestic sector as a whole [14].

2.2.2.1 Top down Approach

The top down model attempts to attribute aggregate energy use data to different characteristics of the residential sector and economy, with the main aim of recognizing long term trends in energy consumption. It treats the whole sector as energy sink and is not concerned with individual end uses [15]. It makes use of historic aggregate energy usage data supplied by energy suppliers, and treats it as a function of top level variables. Variables that are commonly used by top down models include macroeconomic indicators such as population, gross domestic product (GDP), climatic conditions or housing construction and demolition rates [15]. The top down approach is used to provide long-term forecasting, and due to its reliance on historical data, it usually focuses on national levels rather than local levels.

The strengths of the top down approach are: it needs only aggregate data which is commonly available, simplicity, and the ability to identify trends over time when historical data is used. The reliance on historical data is also a drawback since these models have no essential capability to directly model changes that are not reflected in economic or demographic variables, such as improvements in technology or behavioural changes [16]. Moreover, the lack of details about the energy use of individual end uses reduces the ability to identify key areas such as implementation of demand side management (DSM) and meeting a countries commitment to CO_2 emission targets.

2.2.2.2 Bottom-up Approach

Although top down models help to explain trends in whole housing stock energy use patterns, they cannot show the different components that contribute to energy use at the consumer level. For this type of analysis it is required to carry out investigation at the local level. The bottom up method takes a disaggregated approach and predicts energy load data using a combination of physical, behavioural and demographic characteristics for a household [17].

Bottom up method can be categorized into two types which are reliant on the data and structure of the study needed. These types are the statistical method and the engineering method. The engineering model approach is based on building physics. It estimates the energy use of different end-uses by taking into consideration energy ratings and usage of appliances. Statistical methods (SM) are based on historical data and types of regression analysis which are used to attribute household energy use to particular end uses [18-19]. Once the relations between end uses and energy use have been recognized, the model enables to predict the energy demand of households representative of the housing stock.

The detailed data input can be considered the strength of the bottom up approach and enables it to model technological choices. The bottom up model has the ability to predict the energy use of each end use and in doing so can identify areas for improvement. As energy use is calculated, bottom-up approaches have the ability to determine the total energy use of the domestic sector without relying on historical data.

In conclusion, the main dissimilarity between the two approaches is the perspective that is adopted. Top down method starts with aggregate information and then disaggregates down as much as they can. Conversely, bottom-up methods start with detailed disaggregated data and then aggregate this data so far as they possibly can.

2.2.3 Factors Affecting Domestic Energy Consumption

Understanding the main determinants affecting a households' energy use is important for the planning and implementation of efficient strategies to reduce energy use in the domestic sector. There are many factors affecting the energy demand of households. These factors potentially include electricity price, number of electric appliances, income level, weather conditions, the energy systems within the building and the behaviour of the occupants living in the building. The factors affecting the levels of energy use in domestic buildings could be divided into two types of determinants [18,40]:

1- Behavioural determinants: Occupants' behaviour of using energy in a house can significantly influence the household's energy use. The electric energy consumed may slightly relate to weather but is strongly related to households' human factors (occupants' behaviour). The behaviour of occupants towards the appliances they use (switching them off or not at departure, using different appliances at once, their behaviour towards stand by appliances) will play an essential role in shaping the load profile.

2- Physical determinants: The kind of energy consumed, for example, heating, cooling and lighting energy has a high correlation to climate and building design, however a low correlation to occupants' behaviour. The physical factors of energy usage, such as house size, design, and heating system are the result of relatively fixed decisions.

Several authors have previously looked into the characteristics and factors affecting domestic energy consumption [20-29]. In [20] the growth in electricity use was found to be the result of many factors including income levels, energy policy measures, and consumer behaviour. Governments sometimes have promoted using electricity as an alternative for oil in support of energy security reasons. The demand for electricity can also be influenced strongly by the structural changes in the economies of the OECD countries, through the effects of increased personal income, changes in lifestyle, and shifts in the composition of industrial output and developments in production technologies.

In [21] an econometric model with log linear demand function was used to study the monthly electricity consumption for domestic consumers throughout the summer season, for the period from 1972 to 1975. The results showed that the factors influencing electricity consumption were weather, the real price of electricity, and requests for energy conservation. Even though this reference is old, it is still relevant to work with traditional modeling.

The study in [22] split the total household electricity use into four main end uses; heating, ventilation and air-conditioning (HVAC), low power appliances, lighting and lifts. Throughout the hot summer months, it was found that HVAC was the major electricity end use, accounting for about 30-60%, lighting was second with 20-35% and low power appliances was the third with about 15-25%.The lift accounted for the smallest percentage of the total load.

In [23] the relationship between energy use and GDP using annual data from 1971 to 2002 for twenty countries was investigated. The study results explained that an increase in GDP is associated with an increase in energy use in the long term.

In [24] the determinants behind increased household electricity demand in Norway were investigated by using annual consumer expenditure data. The findings showed that, an increase in the number of households, average electricity consumption per household, stock of appliances, income, and number of rooms, were the main factors responsible for the rise in household demand for electricity.

The authors in [25] studied the determinants of aggregate electricity demand in South Africa by using an econometric model throughout the period 1960 to 2007. The results showed that use of electricity was deeply influenced by changes in household income. However, the study found that changes in electricity price had no effect on electricity use. The study found that any government policy for implementing changes in electricity price relies on the factors which affect electricity use.

The authors in [1] presented results from the analysis of responses to an individual household questionnaire survey and associated annual gas and electricity meter consumption data of UK domestic energy-demand. Simple and multiple regressions were used to determine the strength of the relationships and identify the most statistically significant indicators of differences in gas and electricity consumption. No significant effects of built-form type on energy consumption have been observed in the sample of data available. However, the findings showed that the number of bedrooms and regular home-working, have a significant influence on household energy consumption in the UK.

Household electricity use in Taiwan was studied for short and long term periods [26]. The key variables of the study were household income level, electricity price, population growth, and weather. The analysis concluded that in the long term electricity demand increased as household income increased, with price having a negative impact. However, the effects of price and income were smaller in the short term as compared to the long term. Moreover, weather and urbanization influenced electricity consumption in both the short and long term. A study in [27] confirmed this result by making a comparative analysis of the determinants of electricity demand in domestic and commercial sectors for London and Athens, and reached the same conclusion; that social, economic and demographic factors play a key role in demand for electricity.

A study looked at the determinants which brought changes in aggregate electricity demand in Greece for both short and long run periods [28]. The study concluded that in the long run real income, price level and weather played an important role in domestic electricity demand. However, in the short run changes in demand for electricity were influenced only by weather conditions. The author concluded that domestic demand for electricity in future will stay stable in Greece. A study in [29] analysing the factors of household (HH) energy demand in Turkey also concluded that income and price influence electricity demand.

2.2.4 Load Profile Models

Nowadays, load profiling has become one of the most appropriate methods to deal effectively with the consumers' load shape. The aim is to divide consumers with similar load profiles into consistent groups. Load profiling is commonly used for billing, demand predicting, and tariff designs. The choice of the most appropriate load profiling method for any situation depends on factors including data availability, cost, equipment availability, accuracy requirements, regulatory requirements and the needs of the utility distribution company [4].

Several papers present work regarding the establishment of load profiles for a group of consumers [4, 30- 44], which are based on surveys and measurements.
A survey of more than 1000 adults was conducted via a questionnaire in the south east of England by [4] in order to collect information about consumers' ownership levels of appliances, their usage patterns, etc.

A measurement of electrical energy use profiles for the social housing sector in the UK was taken over a period of 2 years [30]. The measurements were all obtained at 5 minute intervals. Annual energy uses, daily and overall profiles were obtained for the dwellings from the data. A survey was undertaken amongst the occupants living in the monitored houses in order to make a link among the energy use profiles and socio-economic issues.

The Swedish Energy Agency [31] recorded appliance consumption data of individual appliances for 400 households in order to understand where and how measures should be taken to increase the number of energy efficient appliances in the homes. This provided accurate consumption data on individual appliances and the results are of sufficient detail to make energy efficiency recommendations.

The patterns of electricity consumption and how occupancy and housing characteristics affect domestic electricity use for 27 homes in various locations throughout Northern Ireland (cities, towns and villages) were studied by [32]. The results of this study showed that there is a strong correlation between average annual electricity consumption and floor area.

A demand side management study in 1999 recorded electricity load profiles for 30 homes every one-minute over periods of 1– 4 weeks [33]. The recorded loads clearly show the effects of different appliances on consumption levels. Similar monitoring studies in the non-domestic building sector (secondary schools) have also been undertaken which identify consumption patterns based on whole building electricity measurements [34]. A study in [35] provided a detailed analysis of the effects of time averaging on eight domestic electricity load profiles at a resolution of one minute. Data were logged and analysed at 1 min intervals at seven houses over two years.

A bottom-up approach was presented by [36]. This was based on relevant socioeconomic factors, demographic characteristics, lifestyles and also appliance ownership, where load curves are constructed from power demand profiles of single appliances. Load profiles for individual houses were generated. The aim was then to aggregate the profiles in order to predict the overall consumption of a group of households in a given area. This information could then be used to predict the response to rate policies and demand side management strategies. Likewise, another study [37] presented another bottom-up model for creating domestic electricity load profiles at individual household level, where the household load profile comprises of individual appliance groups. The input data of the model was based mainly on public reports and statistics. The problem with models having both high temporal and spatial resolutions is the amount of input data needed and the often complicated model structure.

In [38] a model of domestic lighting demand was developed. The model is based on half hourly data measured for a sample of 100 houses in the UK. A modelling approach for generating daily electricity and hot-water demand profiles for households was developed by [39]. A simple method of generating household load profiles (SMLP) for the design of renewable energy systems in the UK was presented by [40]. The input data of the model was based mainly on public reports and statistics, such as the composition of households and average energy consumption of appliances per capita. The UK average size household (3 persons) was selected for this model. Previous study in generating non HVAC (Heating, Ventilating, and Air Conditioning) load profiles at five minute time intervals for three target Canadian households (low, medium and high energy) using a bottom up approach was presented by [41]. A probabilistic approach to characterizing the aggregated load pattern (ALP) of low-voltage consumers in distribution networks was proposed by [42]. This included a load survey which had been performed on a real distribution system.

A high resolution model of domestic electricity load profiles was presented in [43]. This model was based on a combination of occupancy patterns (i.e. when occupants are at home and awake), and profiles of daily activities that describe how occupants spend their time performing certain activities. One minute time interval synthetic electricity load data was generated throughout the simulation of domestic appliance use; the model covers all major appliances commonly used in the domestic sector. In order to validate the model, electricity demand within 22 dwellings in the East Midlands, UK was recorded over the period of a year. A comparison was made between the synthetic and measured data sets; it showed them to have similar statistical characteristics. A paper [44] on micro-grids provided high resolution data for one house and proposed a simple model to generate load patterns for a set of hypothetical households and dwellings.

In general, these models and other high-resolution demand models tend to be complex and dependent on large amounts of input data and assumptions and are therefore not commonly used. The challenge with detailed demand modelling must therefore be to keep the model structure as simple as possible while ensuring sufficiently realistic output data. In particular, there is a need for more general and more realistic model structures in which the demand is based on activities in households rather than the resulting power demand. A major challenge for further demand modelling must be not only to make detailed models but to do it with the lowest possible complexity and need of input data.

2.2.5 Demand Side Management

Demand Side Management (DSM) is the process of planning and implementation of activities designed to influence consumers in such a way that the shape of the load curve of the utility can be modified to produce power in an optimal way. It monitors activities on the consumer's side of the meter to modify the amount or timing of energy use. DSM provides a variety of technical and behavioural solutions to modify electricity use and demand and therefore increases the efficiency and reliability of power systems [45]. Demand side management of the load considers not only technical or economic factors, but also social measures, since these are all related to behavioural issues. Load management measures are both direct and indirect. Direct load management (control) is based on technological measures and controls the load demand by directly switching different appliances on or off. Indirect load control is based on economic measures. Different tariffs and pricing mechanisms are introduced in order to encourage customers to optimise load demand.

Understanding appliance profiles and patterns of use can serve to develop strategies to reduce peaks in demand, easing the potential problems of insufficient generating capacity. DSM includes demand response and energy efficiency measures, such as load management, energy efficiency and electrification activities, and has developed in response to changes in industry structure and policy priorities since the oil crisis in the 1970s [46]. DSM programmes use rates, incentives and other strategies to help better manage electricity use during periods of high peak demand. Demand side management initiatives involving direct participation from the consumer side can bring a significant reduction in electricity prices, as demand-driven shifts of demand during peaks could reduce marginal costs [47]. Several rate design programs have been conceived by distribution utilities to lower electricity rates for consumers. Time of Use rates (TOU) which are based on an hourly or peak/off peak rates are one of the most effective programs. Time differentiated rates apply different demand and energy prices for different daily time periods of use. These rates are based on the theory that the customer should face prices that reflect the cost of service, which is higher when the demand on the system is greater. Different rates may apply on a seasonal basis, or may be expanded to include specific day types.

A generalized tool to assess the responsiveness level among domestic consumers was presented in [48]. The load profiles for different domestic consumers which are composed of power consumption of end-use appliances were studied. The impact of different electricity tariffs on the load profile of domestic consumers was also shown. A 1992 study conducted by the Electric Association in the U.K showed the majority of consumers preferred a time-of-use (TOU) rate tariff and that they adjusted their use of electricity accordingly. As expected, usage was reallocated to the less expensive off-peak periods, while overall monthly consumption remained relatively constant [49].

The Ontario Energy Board Smart Price Pilot was conducted to evaluate customer impacts and reactions to TOU rates [50]. The analysis considered 373 households in Ottawa, Ontario which were placed in three pricing groups: TOU rates, TOU rates with a critical peak period (CPP), and TOU rates with a critical peak rebate (CPR). Under the CPP rate structure, participants were charged 30 cents/kWh for electricity consumed during the critical peak period. Under the CPR rate structure, participants were refunded 30 cents for every kWh reduction below their baseline usage during the critical peak hours. Researchers evaluated the extent to which the various TOU rate structures caused a shift in the customers' electricity usage to off-peak periods and a change in the monthly electricity demand, as well as the customers' acceptance of the rate structure. The results showed that there was a 5.7% shift in load during the four critical peak days during the summer period for participants on TOU rates. For participants on CPP rates and CPR rates, the reduction was 25.4% and 17.5% respectively. Also, the majority of participants (78%) from all rate categories suggested that they would recommend TOU rates to their friends. This study provides significant justification for the introduction of TOU rates in Ontario.

A statistically representative typical single detached Canadian house was modelled by the building energy simulation software ESP-r by [51], in order to estimate 15 min electricity load profile data. This model was used to evaluate the benefits of adopting the time of use price plan under various demand response scenarios. The scope of the study was to present the magnitude of the potential of cost savings by implementing time of use price plans. Also several other studies have recently been published on the benefits of electricity dynamic pricing [52–55].

2.2.6 Occupants Behaviours and Occupancy Patterns

The biggest barrier in utilizing domestic demand response is lack of information regarding the consumers' behaviour and consumption patterns. Occupants' behaviour with regard to energy usage in a house can significantly influence the household's energy consumption. Occupants' behaviour with regard to using energy is a complex issue and presents a big challenge for researchers.

The population is a various group of people each having different histories, attitudes, and socio cultural backgrounds (age, sex, education and income). People also show differences in their physical or mental condition, relationships with family or friends and amount of free time, all of which influences their energy consumption behaviour.

Understanding people's fundamental knowledge of energy consumption, rather than just measured consumption, might also be important, since this will possibly help to determine why some individuals abstain from particular energy use behaviours. Individuals often prefer to buy cheaper less efficient models, because there is usually a price increase associated with the highest efficiency equipment [56], while appliances' producers need to achieve high production rates if sales prices are to be minimised. If individuals consumed less energy before energy efficiency technologies were even used, the combined realized energy savings would be even greater. Therefore, human behaviour should be considered as one factor in achieving greater energy efficiency. However, human behaviour might not be easy to change, particularly when it is in the result of cultural background.

A study by [57] stated that energy consumption may be controlled if consumers have more information regarding their consumption. Domestic consumers decrease their energy consumption when provided with information and feedback on how much they are consuming. On the other hand, a study by [56] argued that energy consumption can be reduced by providing the consumer with a more informed choice about their energy usage. In general, changing energy consumption behaviour has promising potential for energy conservation [58]. Previous work in [59,60] suggested that energy savings can be achieved by locating 'cold' appliances sensibly (e.g. not adjacent to an oven) but once located little can be benefited by changing user behaviour. With 'wet' appliances, consumers can choose different wash temperatures and maximise their washing load per cycle. With lighting, consumers can use more efficient bulbs, use timers and remembering to turn lights off. Therefore, the best ways the consumers can influence wet appliances and lighting system might include on/off decisions and somewhat more complex choices regarding lighting levels and setting wash temperatures.

Energy consumption in twenty eight identical town houses was investigated by [61]. The result indicated that the highest variant in energy use was two to one, i.e. one town house used twice as much as another. Moreover, the energy use depends on the occupants. In another study, the energy consumption in 22 identical houses in Germany was measured over a 2 years period [62]. It was found that the main variation in energy use between 12 of the houses which were ventilated identically was 284%. The house with the smallest use had the lowest mean temperature involving that residents conserved energy by having a lower heating set-point in the heating season. The determinants for space heating system use were studied using a questionnaire survey [63]. It was found that the age, number of occupants, income level, and ownership level influenced the use of oil used for heating. This demonstrates that socioeconomic status has an impact on the behaviour patterns of occupants.

A detailed survey among householders resident in the south east of England was conducted by [4]. The survey focused on ownership levels for certain appliances and their usage patterns, recognizing environmental attitudes and beliefs, and the type of information occupants aim to receive on their energy consumption. The survey findings showed that members of the general public: (i) pay attention when receiving information about their energy consumption and the related environmental impact, and (ii) are willing to change their behaviour to lower household energy use and environmental harm. A similar result was found by [64], in which the energy use of 120 houses in Bath, UK, was observed along nine months. The participants received feedback in diverse forms (i.e. Their consumption compared to previous use or to similar others; energy saving data; or feedback relating to financial or environmental costs). The study indicated that participants who had positive environmental attitude, but who had not previously engaged in energy conservation activities, were more expected to modify their use in response to the energy consumption information.

The authors in [65] observed a significant change in levels of household electricity use in a UK study that monitored electricity use in 72 houses over a period of two years. Categorizing households into low, medium and high energy consumption groups, the study showed that the average annual electricity usage of the high group was over about two and a half times more than the low group in a population consisting mainly of modestly sized social housing. Moreover, annual electricity usage was found to vary by a factor of 8.6 over the whole sample range in the first year of monitoring.

Several studies widely support the concept of occupancy being a key driver of many domestic energy demand models, but the lack of availability of input data is a common issue. A study in [40] considered varieties of physical and behavioural factors to formulate energy load profiles in UK domestic buildings. Five occupancy pattern scenarios were proposed. It was concluded that electricity load profiles depend mostly on the number of occupants and occupancy pattern. The authors in [66] concluded that "occupant characteristics and behaviour significantly affect energy use". A study in [39] explained how time use data (TUS) can be used to represent the behaviour of occupants in dwellings in terms of the appliances in use throughout a relevant TUS activity. The influences of occupants' behaviour and activity pattern on electricity use in Kuwaiti residences were studied by [67]. In this study, occupancy patterns and operation schedules of electrical appliances used in these residences were surveyed by selecting a sample of 30 residences. The study showed that annual energy consumption in the residential buildings is certainly influenced by the lifestyles of their occupants.

2.3 Conclusion

In this chapter, a review of various techniques that have been developed through the years for modelling residential sector energy consumption was provided. Then, factors affecting electricity demand were explained. Finally, an overview of literature regarding consumer behaviour and occupancy patterns was presented.

The literature review has shown that there are various forecasting tools which exist for planners at national level. However, at a local community level, where energy demand patterns may significantly differ from the national picture, planners would be unable to justify local and more appropriate intervention due to the lack of appropriate planning tools. Therefore, in this thesis we need to find a tool that can show the dynamic performance of the load during the day and can be integrated with other technologies.

Chapter 3

Traditional Load Profile Tools

3.1 Background

There are various ways to obtain time series energy use data. Generally, energy consumption data is derived indirectly from utility bills on a quarterly or monthly basis by studying load profiling and forecasting. Alternatively, direct measurement of electricity use can be made to obtain the profiled demand data. The choice of the most suitable methods is usually determined by the availability of data and the intentions that exists with of the forecast at hand.

The purpose of this chapter is to assess households' electricity load profiles based on two different sources of electricity consumption data; first data derived from utility bills on a quarterly or monthly basis and second data obtained through direct monitoring. In this chapter, two cases are described to demonstrate the use of traditional load profile tools. The first case focuses on the use of the regression analysis technique to develop a model for households' electricity consumption on a monthly basis. The model considers the results of previous study as an input data element, in order to predict the monthly domestic electricity consumption by means of consumption data derived from electricity bills. This is followed by the second case which describes an analysis of data obtained from a monitoring study of the electricity consumption of a single family household with two adults and children.

3.2 Forecasting Household Electricity Demand using a Regression Analysis Technique

3.2.1 Data Description

The household data used in this study is formed from two different sets of data; one set for building the general model and another set for monthly forecasting of electricity consumption based on this model. The first data set provides information on the average monthly electricity consumption per unit area for UK households for a one year period. This data set was obtained from a previous study presented by [32] throughout the period from December 2004 to February 2005. The study measured electricity usage using a half hour load meter for 27 dwelling in Northern Ireland to obtain an understanding of how occupancy and dwelling characteristics affect domestic electricity use and also to study the pattern of UK households' electricity consumption [32]. The other data set contains information for quarterly electricity consumption for a group of consumers for the whole year -January through December, arranged seasonally, and derived from consumers' electricity bills. The four seasons are winter (Jan 2009-Mar 2009), spring (Apr 2009- Jun 2009), summer (Jul. 2009-Sep. 2009) and autumn (Oct. 2009-Dec. 2009).

In order to validate the model, we compared the resulting fitted equations for different areas to that of the consumption via electricity bills for different houses. The monthly bill data was collected for seven households, taken from their personal records. Table 3.1 lists the quarterly electricity consumption for seven consumers for a one year period. The heating and hot water systems for the houses are provided by means of natural gas. The average monthly electricity consumption per square meter obtained from [32] is listed in Table 3.2. The seasonal electricity consumption data of the seven households ($H_1$to H_7) is shown in Figure 3.1.

Table 3.1 Quarterly electricity consumption for seven households based on electricity bills

Household	**Seasonal quarterly consumption (kWh)**			
	Winter	**Spring**	**Summer**	**Autumn**
H_1	572.1	429.7	446.1	591.8
H_2	751.0	578.0	346.0	671.0
H_3	919.2	745.3	771.1	863.8
H_4	421.0	343.5	360.6	436.2
H_5	500.8	425.6	425.4	556.4
H_6	695.1	569.3	584.1	737.1
H_7	914.8	782.7	846.9	1073.9

Table 3.2 Average UK household monthly electricity use per square meter [32]

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Consumption (kWh/m^2)	4.6	3.9	3.8	3.6	3.5	3.3	3.25	3.3	3.5	4.2	4.35	4.75

3.2.1.1 Regression Analysis

Regression analysis is a statistical tool that examines the strength of a relation between a dependent variable and one or more independent variables, also called explanatory variables. How much of the movement in the dependent variable is explained by the independent variables. The mathematical model of the relation between the dependent variable and the explanatory variables is known as the regression model. The regression model contains one or more unknown parameters that are estimated using the given data on the explanatory variables [69, 70]. The proposed models using simple regression are described in Equation (3.1).

$$Y(t) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i(t) + \varepsilon(t) \tag{3.1}$$

Where *Y(t)* is the electric load at time t, n is the number of explanatory variables, X_i(t) is the explanatory variables at time *t*, β_i is the regression model parameter and *ε(t)* is the residuals of the regression model.

The fitting algorithm that determines the regression model parameters (*β*'s) in equation (3.1) uses the ordinary least square (OLS) criterion [71].

In this study, the regression technique has been used to build the general regression model which is being used to forecast the monthly electricity demand. The regression equation which relates the explanatory variable is denoted by *M* with the outcome denoted by *MEC*.

$$MEC = f(M) \tag{3.2 }$$

Where; *MEC* is the monthly electricity consumption per unit area (kWh/m^2) and *M* is the month index (1 for Jan., 2 for Feb, ... and 12 for Dec.).

For the time period from January to December, the statistical analysis was used to forecast the general fitted regression monthly electricity consumption per unit area. The response is the monthly electricity consumption data (Table 3.1) which was obtained from [32]. The predictor is the month index.

The computer statistical package software MINITAB has been used to get the fitted regression equation. MINITAB is a widely used software developed by MINITAB

Inc. It can be used for various purposes of statistical analysis [141]. The software tool was chosen as it is widely available in the computer labs of the University and the author has prior experience of the software. The MINITAB output is shown in Table 3.3.

The resultant fitted regression model used to forecast the monthly electricity consumption per square meter as a function of month index is:

$$MEC = 5.044 - 0.5631M + 0.04529M^2 \tag{3.3}$$

The resultant fitted regression plot of the monthly electricity consumption per square meter is shown in Figure 3. 2.

Various statistical tests are used to validate the models. They include the adjusted coefficient of determination R^2 to determine how well the model explains the actual consumption data and F-test for overall significance of the model. Table 3.3 which shows the MINITAB output entails the model summary and presents crucial information about the model, namely, the value of S, R^2 and the adjusted R^2. The coefficient of determination (R^2) measures the proportion of variance in the energy consumption (MEC) that is explained by M (month). The coefficient of determination R^2 is 0.938 which indicates that 93.8% of the variation in household monthly electricity consumption (*MEC*) is around its mean, explained by M (month). The monthly electricity model developed is good with coefficient of determination R^2 of 0.938, but better models may exist as the adjusted R^2 is less than 0.924.

Through the adjusted R^2 we can obtain an idea about the quality of generalization of our model. It would be ideal if its value would be the same or very close to the value of R^2. The value shows that the difference for the model is very small (in fact the difference between the values is (0.938 - 0.924) = 0.014 (about 1.4%). This indicates that the cross-validity of this model is very good.

Table 3.3 MINITAB output regression

Polynomial Regression Analysis: MEC versus M

The regression equation is

*MEC = 5.044 - 0.5631 M + 0.04529 M**2*

S = 0.144632   R-Sq = 93.8%   R-Sq(adj) = 92.4%

Analysis of Variance

Source	*DF*	*SS*	*MS*	*F*	*P*
Regression	*2*	*2.83236*	*1.41618*	*67.70*	*0.000*
Error	*9*	*0.18827*	*0.02092*		
Total	*11*	*3.02062*			

The significance of R^2 was tested using an F-ratio. The F ratio is F = 67.7 and significant at p =0.000 which indicates that the model reflects a real association between the dependent variable (MEC) and the independent variable (M).

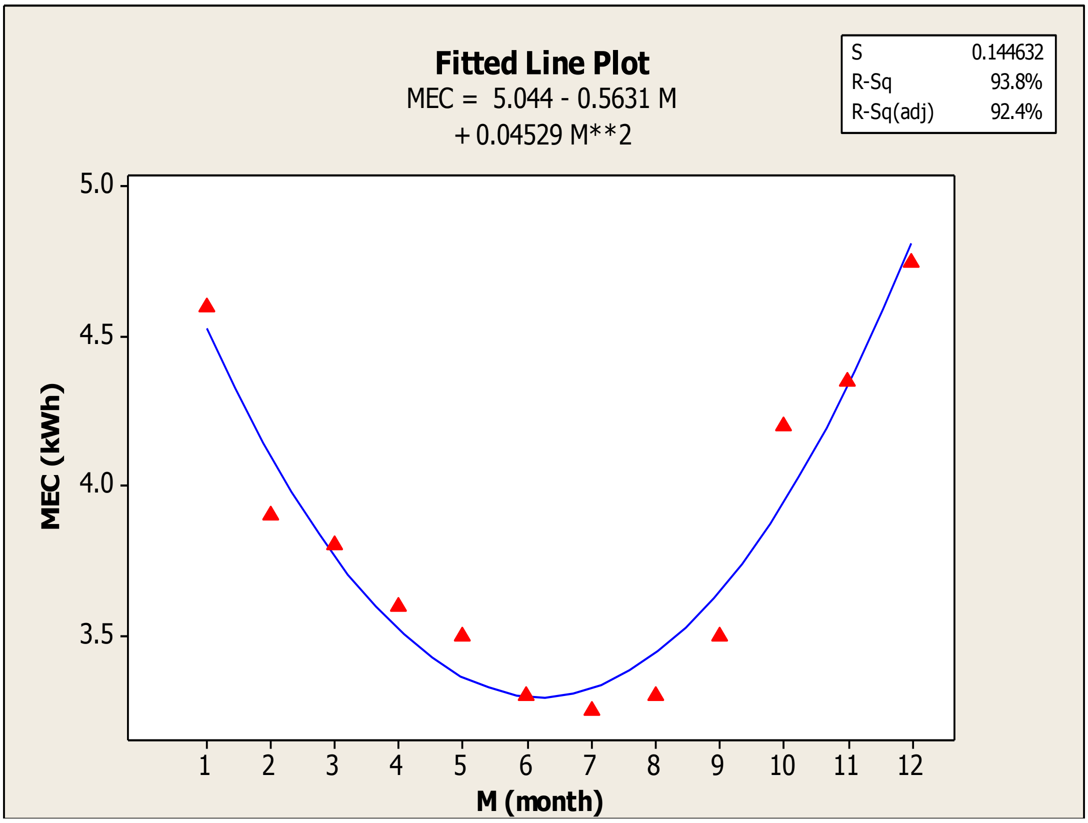

Figure 3.1 Fitted and actual lines plot of monthly electricity consumption per square meter

Figure 3.2 shows the actual electricity consumption along with the predicted values using the models developed. As can be seen, an appropriate fit of the historical data is provided by these models. The residuals produced by these models are also well behaved.

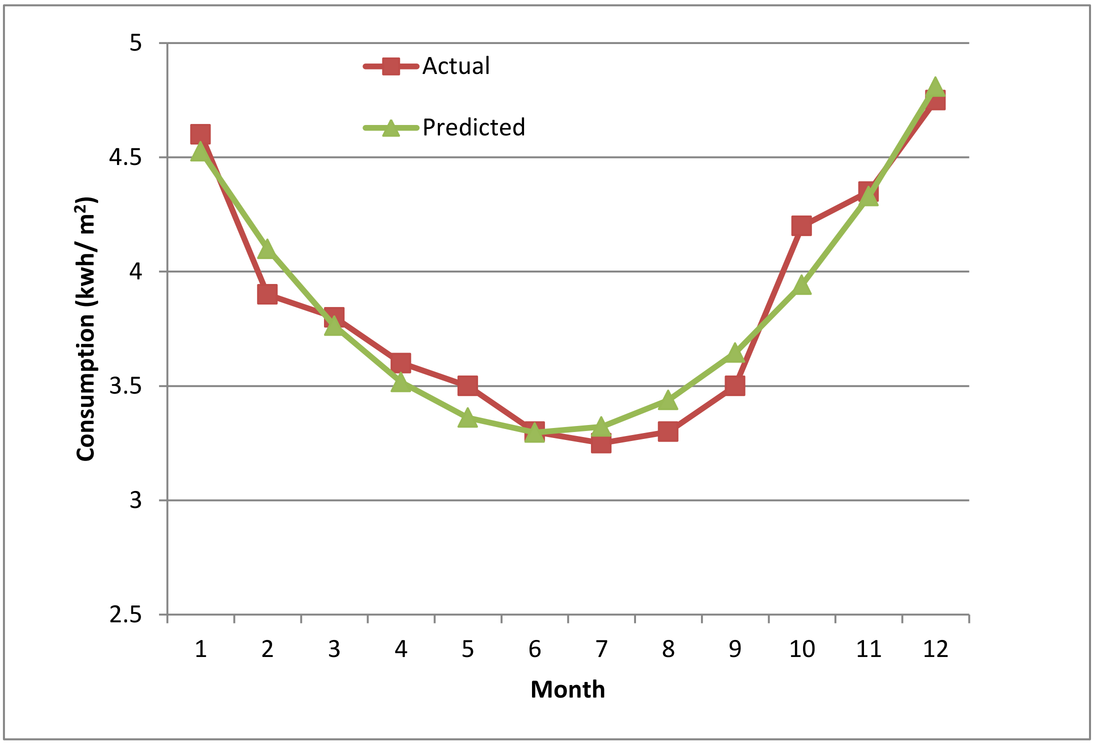

Figure 3.2 Actual and forecasted values of monthly electricity demand

The fitted regression equation for monthly electricity consumption for a house with an area of A (m^2) can be obtained by multiplying the resulting fitted regression equation (Equation 3.3) by the total surface area:

$$MEC' = A(5.044 - 0.5631M + 0.04529M^2) \tag{3.4}$$

Where; MEC' is the monthly electricity consumption per specified area (kWh/m^2).

For example, the fitted regression equation for a house of 100 m^2 area will be in the form:

$$MEC' = 504.4 - 56.31M + 4.529M^2 \tag{3.5}$$

3.2.2 Forecasting of Households' Monthly Electricity Consumption

In this section, we aim to predict the monthly electricity consumption for the selected houses by using the general fitted model shown in Equation (3.5). The prediction is based on electricity consumption derived from households' electricity bills. In order to forecast the households' consumption, it is assumed that the households' monthly electricity consumptions are more likely to have the same pattern (houses of differing areas have differing load consumption but are likely to have the same characteristics). Using Table 3.2; the quarterly electricity consumption for the winter season (from Jan to Mar) for a house with area of 100 m^2 was calculated by multiplying the aggregation of demand during the winter season by 100 which is equal to 1230 kWh.

The fitted regression equation (3.6) has been applied to forecast the monthly demand for different houses with different consumptions. The monthly electricity consumption model can be obtained using the following formula:

$$MEC'_j = \frac{QC_{Bill}}{QC_{Av}}(MEC') \tag{3.6}$$

Where; j is the household number, QC_{Bill} is the quarterly electricity consumption obtained from the electricity bill at a certain period (from January to March) and QC_{Av} is the average quarterly electricity consumption obtained from site measurement of previous study (Table 3.2) for the same period.

The monthly electricity demand model which is based on quarterly billing for seven consumers for the months from January to December (Table 3.1) can be formulated as:

$$MEC'_j = \frac{QC_{Bill}}{1230}(504.4 - 56.31M + 4.529M^2) \tag{3.7}$$

$$MEC'_j = QC_{Bill}l(0.41 - 0.046M + 0.0037M^2) \tag{3.8}$$

Equation (3.9) shows as an example, the monthly electricity consumption for the first household (MEC'_1).

$$MEC'_1 = 572.1(0.41 - 0.046M + 0.0037M^2) \tag{3.9}$$

$$MEC'_1 = 234.6 - 26.18M + 2.1M^2 \tag{3.10}$$

An Excel spreadsheet has been used to predict households' monthly electricity consumption. The fitted (predicted) values of monthly electricity consumption for the seven households are shown in Table 3.4.

Table 3.4 Predicted households' monthly electricity consumption

Month		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Consumption (kWh)	H1	211	191	175	163	156	153	154	159	169	183	200	222
	H2	276	250	229	214	205	201	202	209	222	240	264	293
	H3	316	286	262	245	234	229	229	231	240	254	275	302
	H4	149	135	123	115	111	108	109	113	120	129	142	159
	H5	179	162	148	139	132	130	132	135	144	156	171	190
	H6	252	228	209	196	187	183	185	191	203	220	241	268
	H7	364	329	302	282	270	264	266	276	293	317	348	387

3.2.2.1 Discussion

The fitted values give an idea about the fluctuations of monthly consumption. Table 3.5 shows the fitted values and the residuals for the monthly consumption data of household H1 as an example; the residuals indicate how well the developed model fits the actual data. From the table, it can be seen that the proposed model follows the actual values very closely. The forecasted electricity consumption for the entire period is very close to the actual data. It was noted that the model gives a maximum error of 9.8% in the spring season and a minimum error of 0.85% in winter season. The results clearly indicate that the proposed model forecasts the monthly electricity consumption with a reasonable agreement with the actual dataset.

Table 3.5 Comparison of actual and forecasted monthly electricity use for H_1

Season	**Actual Consumption (kWh)**	**Forecasted Consumption (kWh)**	**Residual**	**% Error**
winter	572.1	577	4.9	0.85
spring	429.7	472	42.3	9.8
summer	446.1	482	35.9	8
autumn	591.8	606	14.2	2.4
Total	2039.7	2094.84		

The percentage of the forecasting error, which is the percentage of deviation of the actual value from the forecasted value, is shown in Table 3.6. The four seasons' actual consumption data for the seven consumers (H_1- H_7) were compared to the forecasted values. From Table 3.6 and Figure 3.4, it can be observed that in winter, spring, summer and autumn the predicted and actual energy demand figures are within a reasonable range, except in summer where there was a forecast percentage error of 82% for the household H_2 where the actual consumption (346 kWh) is much lower than the predicted value (633 kWh) because the occupants of house H_2 were on holiday outside the UK for about 2 months.

Table 3.6 Percentage error of households' forecast

	Forecasting Error (%)			
Household	Winter	Spring	Summer	Autumn
H_1	0.85	9.8	8	2.4
H_2	0.53	7.1	82	14
H_3	0.6	0.5	13.7	3.8
H_4	3	2.5	5	1.1
H_5	2.4	5.8	3.6	7.2
H_6	0.74	0.6	0.9	1.1
H_7	8.8	4.3	1.4	2.1

From Figure 3.3, which shows the actual seasonal electricity consumption for household H_2, it can be seen that the electricity usage drops dramatically through spring and summer. This might be due to the fact that demand for artificial light in the houses is higher in the winter and autumn than in the spring and summer, reflecting mainly the monthly variation in the hours of the day between sunset and going to bed.

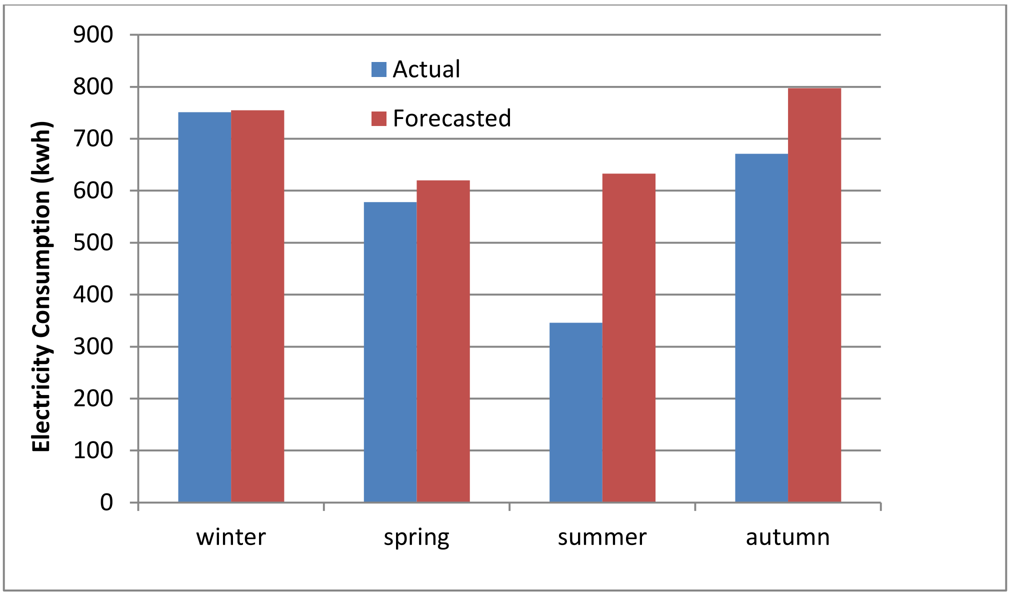

Figure 3.3 Actual and forecasted seasonal electricity use for household H_2

3.2.3 Load Profile from Measurements from a Single Household

3.2.3.1 Data Collection and Measurements

A typical English terraced three storey house was selected for the electricity consumption monitoring. The number of occupants in the house is six (two adults and four children who are of school age). One of the adults is a full time student, the other one is working part time in the morning period in order to take care of the children after school. Measurements of the whole household electricity consumption have been obtained over a period of 12 months for the period from January 2010 to December 2010 in the BD7 area of Bradford, in Northern England. The house space heating, DHW and cooker are all powered by gas.

The measurements were obtained at a high resolution (1 min intervals), moreover the consumption patterns of some individual appliances were also monitored at a high resolution (1 min intervals). Monthly electricity consumption, daily and overall profiles were derived for this household type from the monitored data. The data has been collected using a small wireless handheld portable electricity monitor named owl that enables remote downloading of stored electricity consumption in kWh during 1 minute intervals. The owl wireless monitor uses current transformer sensing technology to sense a small magnetic field around the house power cable. It measures the value of current (A) being passed through the cable and, by reference to the system voltage (230 V), calculates the amount of power being used, the quantity of greenhouse gas emissions and the cost, then transmits this information as CSV files from the sender box to a wireless remote monitor on a wireless frequency of 433MHz, from up to 30 m away (uninterrupted transmission). The data is transmitted periodically to an individual computer via a USB receiver and displayed using the

Owl Home Energy Monitor program. The collected data are exported as CSV files that can be opened up with spreadsheet type applications. The data presented are complete twelve month files including over 500,000 individual data values.

3.2.3.2 Household Load Characteristics

A typical domestic profile over one day at a 1-min resolution and with the corresponding half-hour averages is shown in Figure 3.4. The figure shows that half-hourly average loads are much lower and smoother than 1 min loads. During the period from 00:00 to 07:00 there was a constant cyclical pattern of power consumption between around 100W and 200W which represents the base load. The minimum power consumption of about 160 W represents the power consumption of the continuous appliances and the appliances in standby mode. The continual increase to 200 W was caused by the cold appliances' power consumption. This pattern would be noted regularly throughout the day. From 07:00 to 09:00 the energy consumption was going up as other appliances started to be in use. As there is nobody at home for the period from 09:00 to about 13:30 the base load pattern would be repeated again. However, the second adult is working part time (from 8.00 to 13.00), so, the energy consumption is slightly increased again from the period 13.30 to 15.00. The evening peak period occurs between about 15:30 (time of return home from school) and 21:00, Consumption is more pronounced during this period compared to consumed power at other times when not all the occupants are at home.

The one-minutely average total power consumption showed that, there were several high peaks (spikes) above 1kW that were caused by switching on some electrical appliances with high consumption such as an iron or kettle. The time interval is so short that noise could affect the readings and may cause a few spikes to be added or subtracted from the reading.

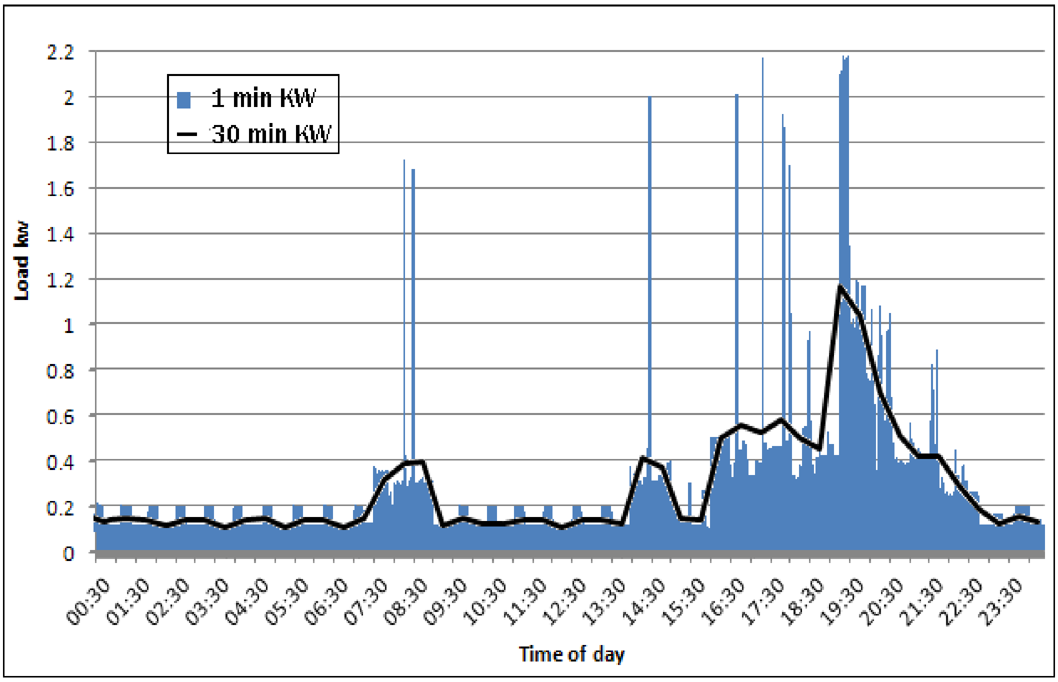

Figure 3.4 Load profile at 1 min and 30 min intervals

To identify with the variety of electricity demand, the daily winter (from Jan. to Mar) and summer (from July to Sep) load profiles logged at 1 min intervals were averaged over 30 min intervals for weekdays and weekends as shown in Figure 3.5 (this has been done in Microsoft Excel spreadsheet). From the figure, it can be seen that, the base load of the demand occurs overnight and is mainly from cold appliances, continuous appliances and appliances in standby mode. The standby appliances are actively switched on by the occupant and their power consumption might not be zero when not in use (e.g. TV). Furthermore there is not a significant difference between summer and winter and weekday or weekend base loads.

The key difference between the weekday and weekend profiles is the period between 09:00 and 18:00, where the load during the weekend profile is higher because of higher occupancy.

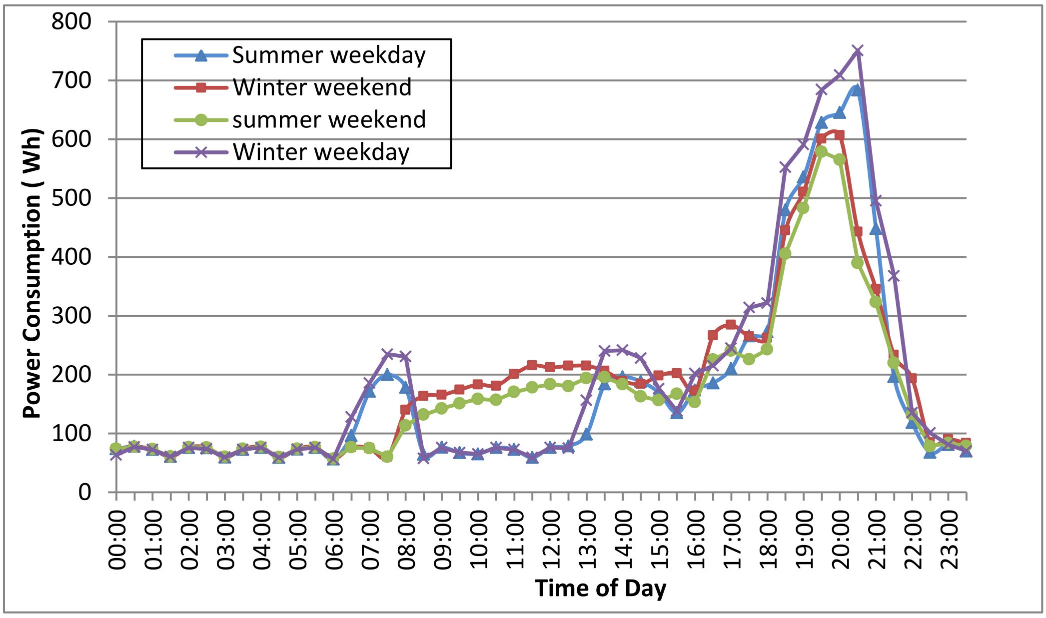

Figure 3.5 Daily winter and summer profiles

The daily electricity consumption of the selected house was measured over a one year period at a high resolution (1 min interval). The seasonal variation of the monthly electricity consumption was recorded. The results for the twelve months are shown in Figure 3.6 where each bar represents the consumption for an individual month. The lowest monthly electricity consumption was about 212 kWh in August while the highest monthly electricity consumption was about 269 kWh which occurred in December. The average monthly electricity consumption was 238 kWh which is lower than the UK Government estimate of average monthly electricity consumption of UK houses (320 kWh in 2008) which reflects the fact that the house space heating, Domestic Hot Water (DHW) and cooker were powered by means of gas.

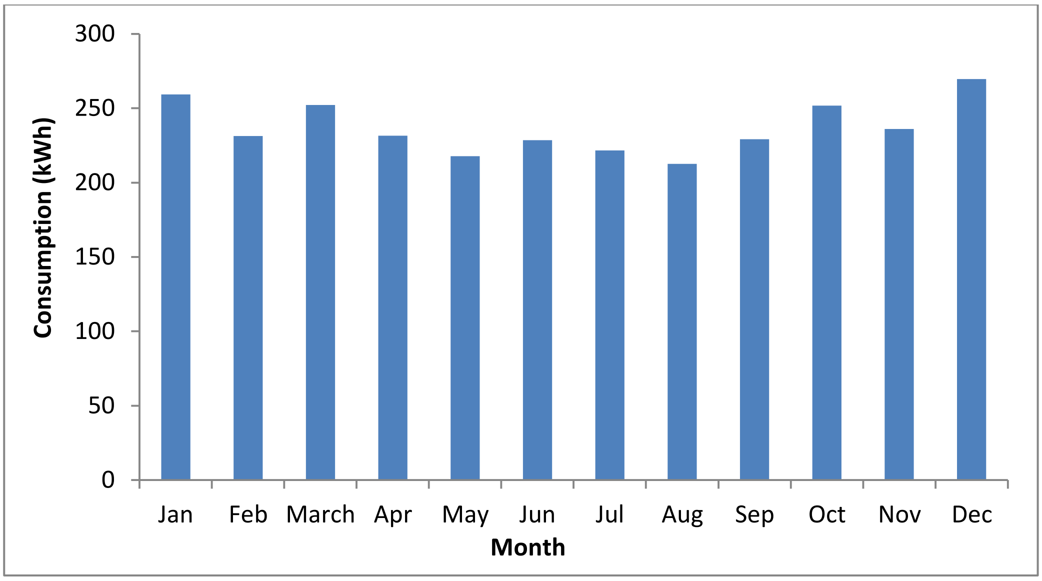

Figure 3.6 Monthly electric energy consumption

3.3 Conclusion

The use of traditional load profile tools was demonstrated. There are various ways to obtain time series energy consumption data. Profiled demand data can be obtained indirectly through forecasting (Indirect Profiling) or directly through measurement (Direct Profiling).This chapter has discussed the use of the traditional load profile tools in two cases.

The first case investigated the forecasting of households' electricity demand by using regression analysis techniques. It demonstrated that, the simple regression method (trend extrapolation method) assumes that things will keep changing in the future the way they have been changing in the past. Therefore it is important to first determine the general trend. This method is observed to be suitable for short term forecasting, but for planning purposes does not address changes.

In the second case the analysis of electrical energy data measured at 1 min intervals over a period of one year for a sample household of two adults with children has been described and investigated. The effects of time averaging were considered. Detailed electricity load profiles for domestic buildings are an important requirement for the accurate analysis of demand side management.

The choice of the most suitable method for analysis is usually determined by the available data sources and the intentions of the forecast. Measurement results in the most accurate profiled data, at the expense of installing measuring equipment and the time required in obtaining data. Moreover, the effort involved in installing, testing, downloading data and checking for data quality is high.

Traditional methods do not study the behaviour of people. The issue is that different households have different behaviour. Therefore, traditional forecasting methods are not suitable for an intervention approach at local community level because there is no clarity on how the intervention could affect behaviour. So, there is a need for a tool that can link the behaviour of households for local planners. This then, is what the next chapters will be addressing.

Chapter 4

Statistical Predictions of Electric Load Profiles in a Virtual Community

In this chapter, a methodology of generating artificial but realistic load profiles at half hourly time interval for a community is presented.

4.1 Electricity Consumption Models

Suitable planning and management for energy at community level can give considerable environmental and economic benefits. Community groups have a considerable impact on increasing the use of sustainable energy practices, adopting demand side management (DSM), raising awareness of climate change, and helping people understand the role they can play in reducing carbon emissions. One of the main barriers is the absence of community load profile data, as usually no measured data are available.

Decision makers increasingly realise that many of the solutions to improving energy consumption performance need to be much more local than national. Local solutions are often very successful, as they reveal the needs of specific communities and get people to participate in taking action in order to help communities become more energy self-sufficient and help facilitate the reduction of CO_2 emissions.

The literature review presented in Chapter Two shows that research into modelling of domestic energy consumption can be grouped into three sections. The first section focuses on using statistical techniques to understand the factors that influence domestic energy consumption using top-down approaches [17-28]. The second section looks at the residential energy consumers' behaviour and how changes in behaviour could help to control a household's energy consumption [4, 39-40, 56-67]. The third section looks at load profile models of the domestic sector [29-44].

A bottom-up model was presented in [36], where load curves are constructed from power demand profiles of single appliances. This model is considered powerful because of taking into consideration factors such as psychological and behavioural characters, but a usual limitation of this model is the need for extensive data about the domestic appliances and how they are used by the homes' occupants. Another bottom-up model presented in [37] uses statistical mean values and general statistical distributions, which lowers the model precision, but also decreases the amount of data needed. The data needed includes the mean electricity consumption rate and seasonal variation with a weekly resolution. The limitations of the model presented in [37] are; that it does not use occupancy as an input, the amount of input data needed is extensive, and the often complicated model structure.

A remarkable load profiling study in the UK domestic sector was presented in [40]. The study considers composition of a household's size, occupancy patterns, and the energy use of domestic appliances and hot water. The authors introduced a simple method to formulate a daily household electrical loads profile (SMLP) for the average number of persons per household in the UK. The generation of the residential electricity load profile is based on five approximate occupancy scenarios. The modelling results of a UK average household appliances load profiles are shown in Figure 4.1.

This method can be applied at both individual household and community level. The limitations of the method presented by the authors in [40] are the lack of consideration of behaviour change data, the lack of consideration of household occupancy patterns and the fact that it represents a limited number of scenarios, which may not necessarily correspond to scenarios in the real community.

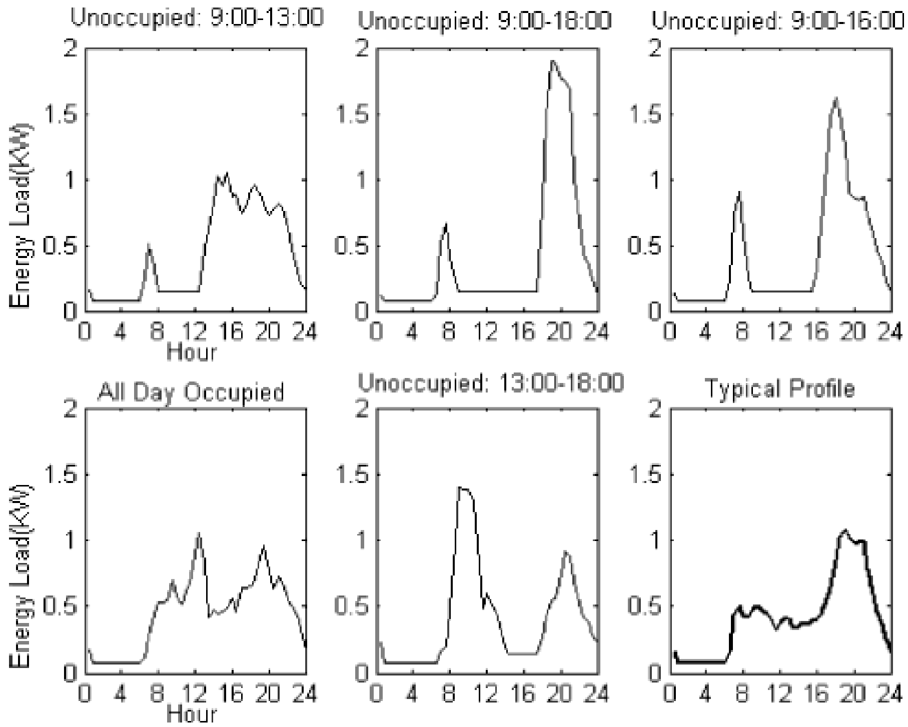

Figure 4.1 Electricity load profiles of UK average size domestic household [40]

There is a need for more general and more realistic model structures in which the load profile is based on actions in households rather than the resulting profile. A major challenge for such further demand modelling must be not only to make detailed models but to do it with the lowest possible complexity and need for input data.

To address this lack in research we have developed a household model that generates realistic electricity load profiles by applying a bottom up load model similar to that in

[40]. In both models the household appliances of each individual household are simulated separately. Then these load profiles are aggregated to generate artificial but realistic load profiles at half hourly time resolutions, first at individual household level, then at community level.

In this thesis, the methodology used to predict daily load profiles at community level is based on the cumulative distribution function which describes the usage times of the appliances in order to generate the random nature of consumption. The cumulative distribution functions are based on real values of a sample population.

4.2 Load Profile

Load profiling is the procedure of describing the pattern of electricity use for a consumer or a group of consumers over a given period of time and can be considered an essential source of information on which energy decisions are made [72]. This information is available in a range of forms, relating to the way in which it is used. The time period could be daily, weekly, monthly or yearly, with a definite time resolution such as hourly or daily. In other words, load profiles demonstrate the relationship between consumer behaviour during the day and the resulting energy demand. Figure 4.2 below shows a graph of the typical domestic load for electricity in the UK [74]. This shows 48 half hour settlement periods during a 24 hour day.

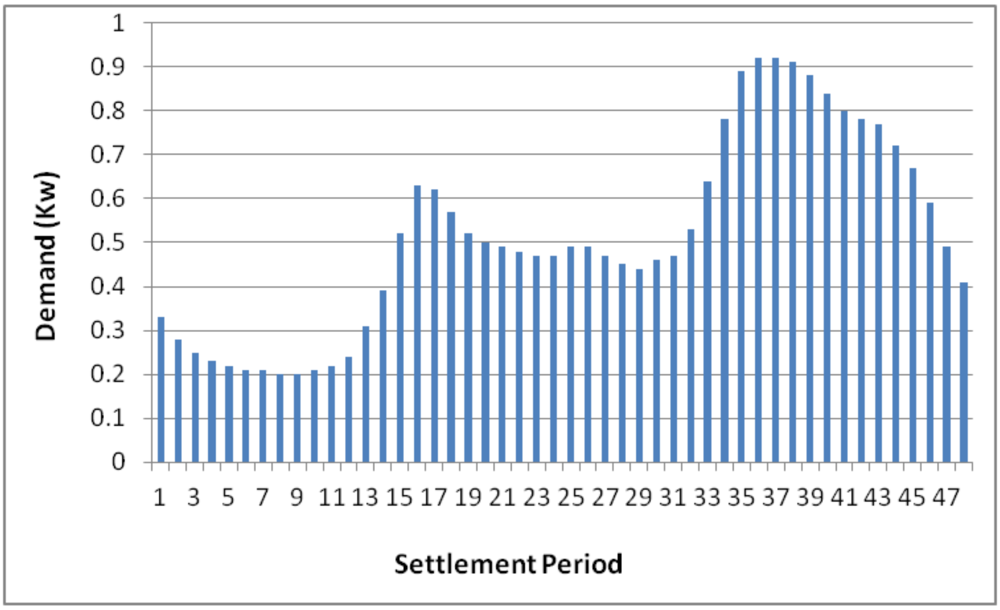

Figure 4.2 A typical daily pattern of demand for the average domestic unrestricted consumer [74]

The concept of load profiling has been used as an efficient tool for energy tariff scheme design, planning and load management. It has emerged as one of the most appropriate methods to deal with the shape of consumers' load profiles. It involves two main actions [73]:

- Determining an approximation of the average load profile of a group of consumers over a known period of time, and
- Allocating that load profile to all consumers in that consumer type.

4.3 Methodology and Data

Modelling of domestic energy consumption relies on input data from which to calculate energy consumption. The level of detail of the available input data can vary dramatically, resulting in the use of different modelling techniques which seek to take advantage of the available information.

The creation of daily load profiles is based on various assumptions. The profiles were created for a virtual community with different household types which have different consumption behaviour. Different households have different lifestyles, which mean consumers of differing types and characteristics have differing daily load profiles. The process of creation of daily load profiles basically starts with the number of households in the community as initial input. Depending on the modelling methodology to be used, the input data required to develop the domestic energy model includes information on demographic information, annual electricity consumption patterns and daily occupancy information.

The methodology presented in this chapter uses cumulative distribution functions (CDF) to describe the usage time of the appliances for different groups of consumers and give a complete description of the probability distribution of their random operations. This represents the probability of a household performing a specific activity during any hour of the day. The cumulative distribution functions are based on real values from a sample of households' occupancy surveyed data describing when and how occupants are likely to be utilizing their electrical appliances at different times of the day. Daily load profiles from individual dwelling to community can be predicted using this method.

4.3.1 Algorithm Description

The total daily energy consumption resulting from utilising electric appliances is calculated as shown in Equation (4.1).

$$\sum_{i=1}^{I} E_i(t) = \sum_{i=1}^{I} N_i(t) \times E_i \qquad (4.1)$$

$$E_D = \sum_{t=1}^{48} E_i(t) \qquad (4.2)$$

Where $E_i(t)$ is total energy consumed by appliance type i at time t, N_i *(t)* is the number of connected appliances type i used at time t, E_i is the energy consumption per time of usage of appliance i and E_D is the total daily energy consumption of households on a half hourly basis.

Electricity use is primarily the result of the utilizing of various types of owned appliances such as electric kettles, computing equipment and lights, which are controlled via users' behaviour by being turned on or off.

Generally, all electric appliances are connected in parallel with each other and supplied by the main power source, as shown in Figure 4.5. Each appliance is connected via a switch and consumes power only when the switch is closed and will be out of use when the switch is open. Therefore the operation of each appliance is reliant on the probability of turning the switch on or off.

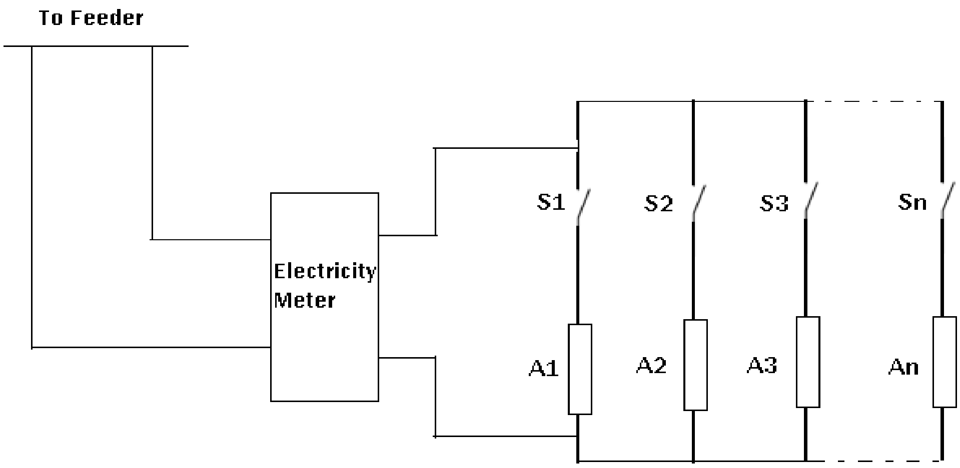

Figure 4.3 Simple diagram of electric appliances in a house

The probability of the switch being on or off is shown in Equation (4.3) below.

$$P(S) = \sum_{j=1}^{8} \sum_{t=1}^{48} \tau(HH_j, t) \times P(HH_j) \tag{4.3}$$

Where P(S) *is* the probability of turning the switch(S) on, τ (HH_j) is equal to 1 when the household type *j* is at home at time *t* , and $P(HH_j,t)$ is the probability of utilization of appliance *n* by household type j, at period t. So, *P(S)* is equal to zero when τ (HH_j, t) equals zero, and will be equal to $P(HH_j, t)$ when $\tau(HH_j, t)$ is equal to one.

$$\tau(HH,t) = \begin{cases} 1 & \text{when the house is occupied (e.g early morning or evening).} \\ 0 & \text{when the house is occupied (e.g day time or after mid night).} \end{cases}$$

The cold appliances such as fridges and freezers have to be switched on all the time which means, there is an exemption for them as the occupancy of consumers does not have a big influence on their operation, assuming the opening or closing of the cold appliance's door has no impact.

4.3.2 Creation of Virtual Community Data Inputs

A community is a social group of any size whose members live in a particular area, share a government, and have common cultural and historical traditions; or a social, religious, working, or other grouping which has common characteristics or interests.

Community energy initiatives can be categorised, for example, in relation to their focus on improving the energy system: energy efficiency, renewable energy technologies (RETs) and behaviour change. Community groups can play a vital role in reducing energy dependence, increasing awareness of climate change, and helping people understand how they can participate effectively in reducing CO_2 emissions.

The model of the electricity load profile for the virtual community uses data from three main input sources:

- Demographic information: The information on the type of households is required such as the number of adults, working people, and number of children.
- Annual electricity consumption patterns: Includes ownership level of appliances, and total energy consumption of certain appliances.
- Daily Occupancy information: This is the behaviour of occupants in households with respect to their usage of appliances and lighting on a daily basis.

4.3.2.1 Demographic Information Required

The Census data available at the UK Office for National Statistics (ONS) is used as the primary information [16]. The Office for National Statistics (ONS) is the executive office of the UK Statistics Authority, a non-ministerial department which reports directly to Parliament. ONS compiles information about the UK's society and economy which provides evidence for policy and decision making, and the allocation of resources. Social Trends offers up to date statistical data on population changes. It is available electronically on the National Statistics website; www.statistics.gov.uk/socialtrends.

The population of the UK was 62.3 million in mid-2010, with an average household size of 2.4 persons. The forecast for the UK population growth from 2010 to 2030 is shown in Figure 4.4. The ONS projection shows that the current UK population of 61.4 million would rise to 67 million by mid-2020 and should the same trend be maintained beyond 2020 then the UK population could rise to above 72 million by mid-2030 (Figure 4.4).

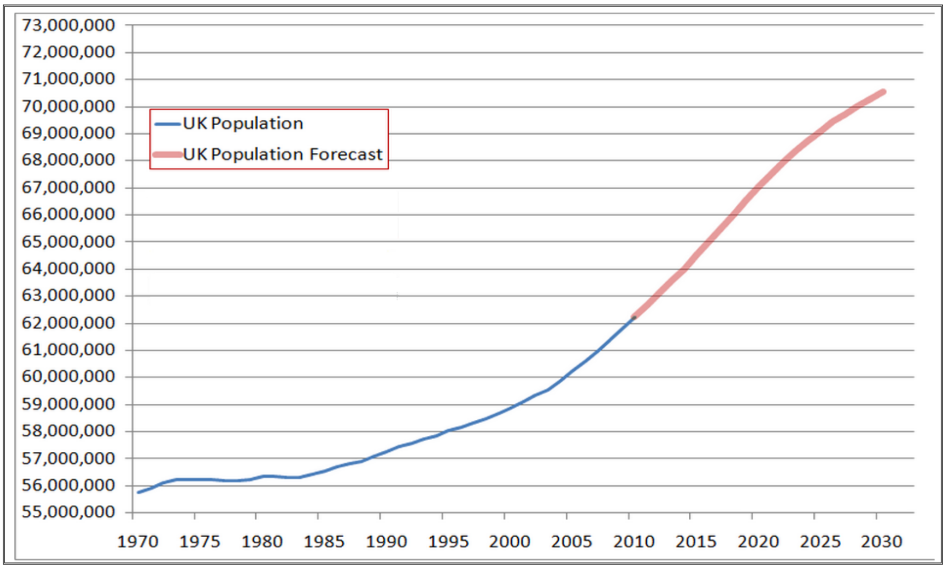

Figure 4.4 Percentage UK population growth forecast 2010 to 2030 [16]

For this generator, the household types have been chosen to be used as scenarios for prediction. A household is defined as a person living alone or a group of people living at the same address who share common housekeeping or a living room, whether related or not [7,75]. There were about 26.0 million households in the UK in 2010. The number of households has increased by 6.1 per cent since 2001, slightly faster than the 4.5 per cent growth in the size of the UK population over the same period. This is due to the trend towards smaller household sizes: the proportion of households containing one person increased from 28.6 per cent to about 30.0 per cent over the period 2001 to 2010. Table 4.1 shows the UK household composition in 2008 by the type of household. It can be seen from the table that, in the UK, couples with no children or with children who represent 22 per cent and 19 per cent respectively are the most common household occupants. The next most common household type is a single adult without children household working or retired adults which represent 16 per cent and 14 per cent respectively.

Table 4.1 Percentage share of household type

Type of Household	Percentage Share (%)
Single adult without children	16
Single adult with children	5
Single retired adult	14
Two adults without children	22
Two adults with children	19
Two retired adults	10
Two adults or more without children	9
Two adults or more with children	5
Total (%)	100

4.3.2.2 Electricity Consumption Patterns of Domestic Appliances

Electricity use in the residential sector has increased dramatically as ownership of electric appliances such as fridges, electronic games and tumble dryers has increased. Efficient energy usage is affected by the choices people make about owning various appliances and the way the appliances are used. Electrical domestic appliances can be generally divided into six groups: brown goods, cold appliances, cooking appliances, wet appliances, miscellaneous appliances, and lighting. Table 4.2 lists the different categories of domestic electrical appliances.

Table 4.2 Domestic appliances categories

Brown goods	electronic consumer goods : TVs, VCRs, radios, clock radios, X-boxes (games), etc.
Cold appliances	refrigerators, freezers, and combined fridge-freezers.
Cooking appliances	electric ovens, electric hobs, and microwaves, etc.
Wet appliances	washing machines, tumble dryers, and dishwashers.
Miscellaneous appliances	vacuum cleaners, irons, electric showers, PCs, garden equipment, hair dryers, sewing machines, torches, drills, battery chargers etc.
Lighting	lights

The ownership levels of electrical appliances are also presented by household. Figure 4.5 shows the ownership level of domestic electrical appliance by household in the UK. This information was obtained from [4], and was updated using data from the Department for Environment, Food and Rural Affairs (DEFRA) [76]. The tags marked '*' are the updated ones. From the figure, it can be seen that the majority of households own a television, kettle, vacuum cleaner and iron, around 75% own a video recorder, 55% own a freezer, approximately 57% own a refrigerator, 64% own an electric oven, 85% own microwaves and 45% own an electric hob (consumers generally prefer to use gas hobs because they are believed to give more flexible control of temperature). In order to produce a daily load profile for different households, the ownership level of domestic appliances was assumed to be the same for different types of households.

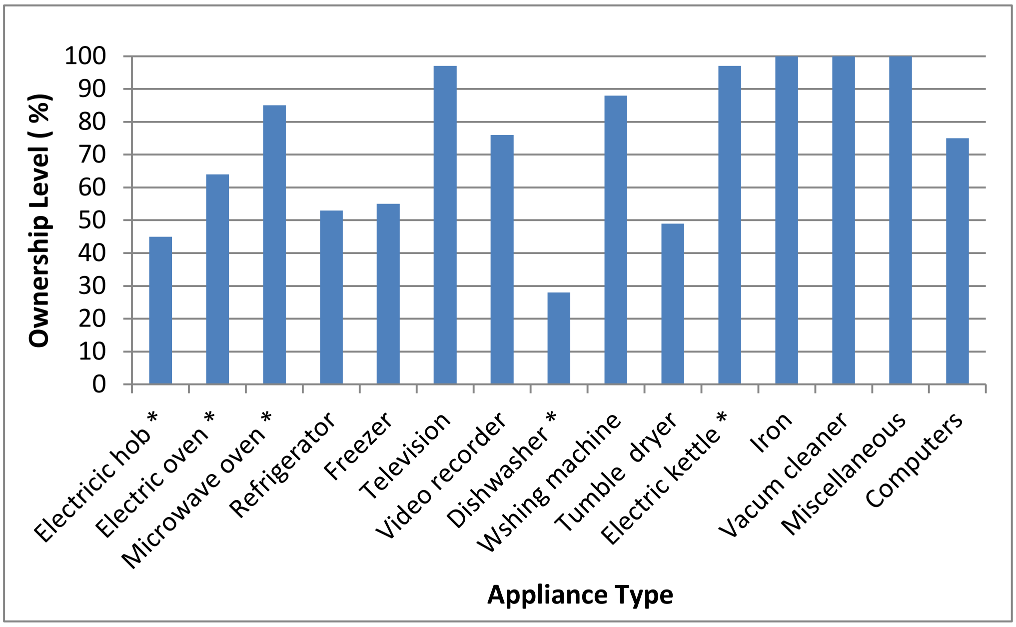

Figure 4.5 Ownership level of domestic appliances

The information on the average daily consumption for key appliances in UK households was obtained from research on energy use carried out in [4]. The information provides the type and the average annual daily consumption per household, the average annual energy use per capita per day and the ownership rate. Table 4.3 lists the average energy consumption of appliances in the UK. The consumption is given by households as well as by per capita. Cooking appliances' and wet appliances' activities are accountable for the majority of the peak load in houses [3].

Table 4.3Average energy consumption of electrical appliances in the UK [40]

Appliance	Average consumption per household (kWh/day)	Average consumption per capita (kWh/day)
Electric hob	1.33	0.39
Electric oven	0.74	0.22
Microwave oven	0.23	0.07
Refrigerator	0.82	0.33
Freezer	1.9	0.55
Television	0.91	0.27
Video recorder	0.3	0.09
Dishwasher	1.72	0.48
Washing machine	0.8	0.2
Tumble driers	0.78	0.28
Electric kettle	0.78	0.28
Iron	0.3	0.09
Vacuum cleaner	0.15	0.04
Miscellaneous	1.1	0.33
Computers	0.5	0.3

4.3.2.3 Daily Occupancy Information

Occupant behaviour has a significant impact on the energy use of households. The occupancy level of dwellings is an important parameter to know in order to determine the energy use. The usage of electrical appliances within buildings varies significantly with respect to time, mainly in accordance with the activity of the building occupants. In the domestic sector, the energy usage is related to the occupancy and depends on the number of occupants, how they behave in their homes and the unoccupied period during the day. Occupants influence the use of electricity by the number of electrical appliances they own and through their use of the appliances. For example, when there is nobody at home; most appliances will not be in use. A daily appliance electricity profile shows that occupants consume practically low power during the night (only cold appliances). Occupants get up, prepare and have breakfast and leave the house during the morning and then may come home again around lunch time. In the evening, many activities are done: cooking the meal, taking a shower and watching television, etc. The household occupancy pattern can be influenced by many factors such as:

- Number of people living in the house.
- The getting up time in the morning and the sleeping time.
- The period of time the house is vacant during the day.

It is important to identify the type of households when analyzing the load profiles, because the load profile depends very much on the occupancy pattern. Due to the lack of information about household occupancy patterns, it was decided to make assumptions for the most common scenarios of household occupancy patterns in the UK. Eight scenarios which present the most common occupancy patterns in the UK have been assumed based on household type. Table 4.3 lists these possible scenarios.

In the domestic sector, a better understanding of consumer behaviour or the usage behaviour of the different parameters of the domestic load is required. One of the main difficulties of domestic demand response is the lack of proper understanding of consumers' behaviour. The daily occupancy information available in the literature is limited, so simpler assumptions have been made for each scenario. For the assumed profiling scenarios, three occupancy profiles have been used: continuous occupancy, vacant throughout working hours and a late. Although the load profile of the cold appliances usually fluctuates throughout the duty cycle of these appliances, the assumption of a constant load is assumed suitably precise [27]. The remaining appliances will have discrete events where the appliance is switched on and utilized. A questionnaire survey was designed to investigate this.

Table 4.4 Scenarios profiles & occupancy assumptions

Scenario	Household Type	Unoccupied period & Assumptions
1	1 working adult	08:30 to 18:00
2	1 retired	The house is occupied all the time
3	1 adult with children	08:30 to 13:30, the occupier is a part time worker
4	2 working adults	08:30 to 18:00
5	2 working adults with children	08.30 to 13.30, one adult has full time job. Other may have a part time job in the morning to take care of the children after school.
6	2 retired	The house is occupied all the time
7	3 adults or more	13:00 to 18:00, two members have full time jobs; the other has a part time job in the afternoon.
8	3 adults with children	The house is occupied all the time, two adults have a full time job and the other one is retired.

4.3.2.4 The Questionnaire Survey

A household energy questionnaire survey was carried out in the BD7 area in Bradford on ninety eight households from the 1st of August 2009 to early September 2009 to generate data regarding household energy consumption patterns. Eighty seven (87) out of ninety eight (98) participants completed and returned the survey. The questionnaire survey used is presented in Appendix A. It is a three pages survey form.

The first aim of the questionnaire survey was to collect specific data to find out when and how many occupants switch on electrical appliances during different times of the day. The results of the survey will help us to get probabilistic estimates of usage of electrical household appliances. It is intended to make a model that gives domestic appliances' electrical load profiles.

The survey questions were divided into three main sections. The first section requests general information about the household to give an overview of household type and occupancy patterns. The second section requests general information about the use of electric appliances in order to collect specific data on when and how often occupants use their electrical appliances at different times of the day. The third section aims to gather information about lighting use.

The questionnaire explained the reason for the research and also explained that the survey was being carried out as part of a PhD project. Participants were assured of the anonymity of their responses.

Analysis

The information from the section of general information about the household is illustrated in Table 4.4. The survey shows that the most common type of household was a couple of adults without children, which accounted for about 24 percent of households. The second most common type was two adults with children, which accounted for about 19 percent. The next most common household type is a single working adult without children which represents 15 percent. A household with more than two adults with children represents the lowest share; 3 percent.

The types of households of respondents were compared with the 2008 Census data, available at the UK Office for National Statistics (ONS). From the table we can note that there is a reasonable agreement between the percentage share of the surveyed data and the percentage share of the national statistics.

Table 4.5 Occupation of the surveyed households

Household Type	**Questionnaire Survey**		**National Statistics**
	No. of households	Percentage share (%)	Percentage share (%)
Single adult	13	15	16
Single retired	13	15	14
Two adults	21	24	22
Two adults with children	17	19	19
Two retired	8	9	10
More than two adults	7	8	9
More than two adults with children	3	4	5
Single adult with children	5	6	5

4.3.2.5 Daily Energy Consumption of Appliances

The daily energy consumption of different types of household electrical appliances was calculated based on average annual consumption per day (per capita or per household depending on the household type as listed in Table 4.3). Each of the appliances listed in Table 4.2 (refrigerator, freezer, dishwasher, clothes washer, clothes dryer, etc) were simulated individually and then combined to generate a random half hourly daily load profile for each household type. In the surveyed households, the heating and hot water systems are provided by means of natural gas. Although the boiler uses an electric powered burner, the electric consumption of this burner is too small and has not been considered. Furthermore, In order to generate appliances load profiles we assumed that the ownership level of each appliance is similar to that of the UK national ownership level and each household has been assumed to have only one of each appliance listed above (Table 4.2).

4.3.3 Electric Lighting Patterns

Artificial lighting provides a wide variety of benefits in houses. It allows activities to be conducted without daylight and creates different interior lighting atmospheres to meet occupants' needs. Lighting use is dependent on the occupancy pattern and is highly affected by daylight conditions (seasons) and the presence of active occupants, e.g.in winter, people need to switch on the artificial lighting in the morning for their activities, but in summer due to the daylight no artificial lighting is required. The lighting loads were calculated based on the survey. Houses were assumed to be using more efficient light bulbs. The following equation can be used to calculate the electric lighting energy consumption (E_l):

$$E_l = N_b \times E_{rb} \tag{4.4}$$

Where N_b is the number of light bulbs per household distributed between bedrooms, kitchen, living room, bathrooms and others, and E_{rb} is the energy rating per bulb per hour. The number of hours during which the light sources in each room consumed energy was obtained from the questionnaire data.

4.4 Generating the Load Profile

4.4.1 Household Type Allocation

In this study, we are generating a load profile for a virtual residential community of 400 different types of household. Given the diversity of people in the UK population, it is almost certain that different households have different levels of knowledge about electricity consumption, different attitudes and different energy-using or saving practices.

To get a picture of the demographic characteristics of the area in order to allocate different numbers of households, the calculation was based on the percentage share of surveyed households (Table 4.5). After calculating of the number of households, the physical location of the households was then allocated randomly using Excel's rand function. Figure 4.6 shows the projected number of each type of household for the assumed community.

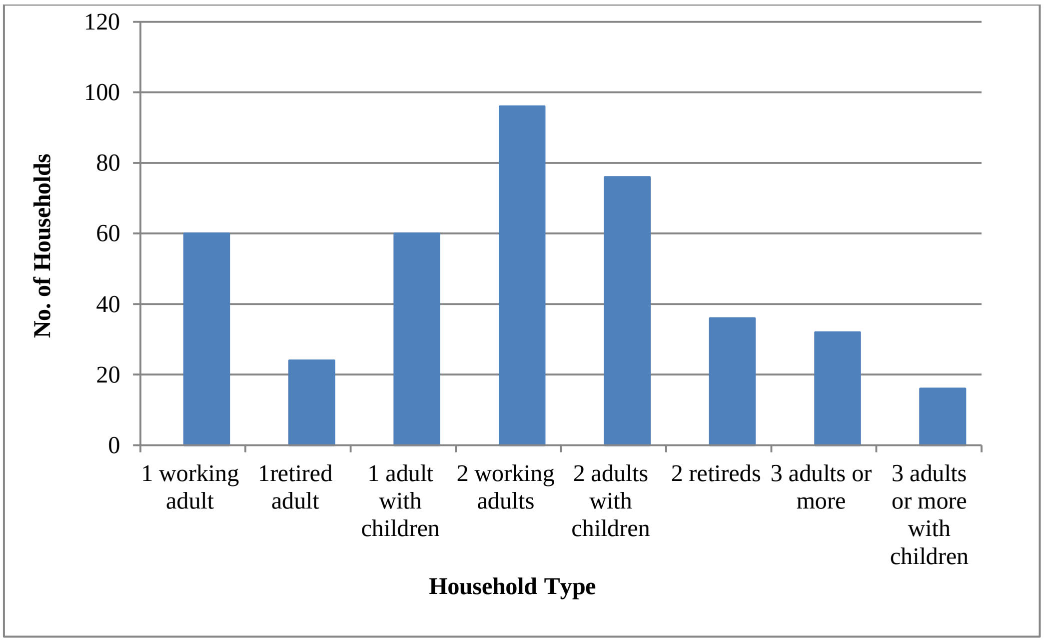

Figure 4.6 Projected numbers of households

4.4.2 Time of Use Probability Profiles

The time of use probability profiles attempts to quantify the probability of the specified activity being undertaken as a function of time of day. The probability profiles represent the probability of a household carrying out a particular activity during a 24 hour period. Occupancy profiles inform the appliance time of use probability which illustrates when an appliance is in operation at a given hour of the day. In order to compute relative probabilities, the survey dataset is filtered to only include information about when and how the occupants use their electrical appliances during different times of the day.

Generally, the relative probability of an event could be approximated by the relative frequency, or fraction of times that the events occur. Relative frequency is the number of times an experimental event occurs, divided by the total number of trials [77]. Relative probability is given by the following equation:

$$P_R \approx \frac{N_x}{N_t} \tag{4.5}$$

Where P_R is the relative probability, N_x is the number of times an event x occurred, and N_t is the total number of trials.

The appliances are physically allocated to households based on the national ownership levels and using the random function. The random nature of electricity load profiles is generated by using cumulative distribution functions (CDF) which describe the usage times of the appliances. The cumulative distribution functions are based on real values of a sample of the population. Figure 4.7 shows the approximate probability and cumulative distribution functions (CDF) of first usage times per day of an electric hob for the single adult household, which resulted from questionnaire survey analysis. This data is obtained from the questionnaire survey of the BD7 area. In other words the behaviour is being predicted on the basis of a particular community. Hence, the assumption is that the 400 households in the community have similar behavior with respect to appliances as the BD7 community.

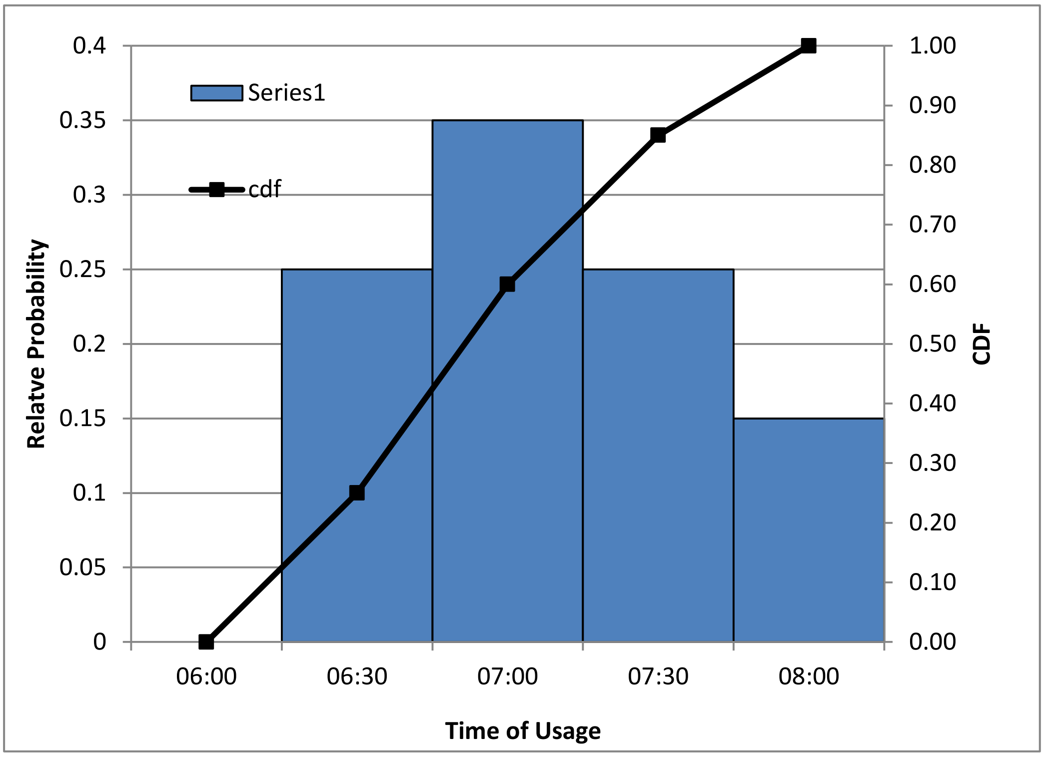

Figure 4.7 Relative probability & cumulative distributive function of first usage times per day for a hob for the single adult household

4.4.3 Generation of Electricity Load Profile

The random creation of load profiles is implemented in Excel on a half hourly basis in order to generate daily electrical load profiles for the eight household types.

Microsoft Excel is a powerful and widely used Spreadsheet software developed by Microsoft [142]. Excel is a spreadsheet application with special features for performing calculations and providing a wide variety of graphics, making it one of the most popular and widely used PC applications [143]. The inbuilt numerical or statistical functions formed in Excel are sufficient for our purposes. Excel was chosen for its simplicity, the universal availability and the author has prior experience of the software.

Figure 4.8 shows the outline of the generator. From the figure, it can be seen that the number of households in the community is the initial input. The number of household types is then calculated using external data from surveyed households, giving the composition of households.

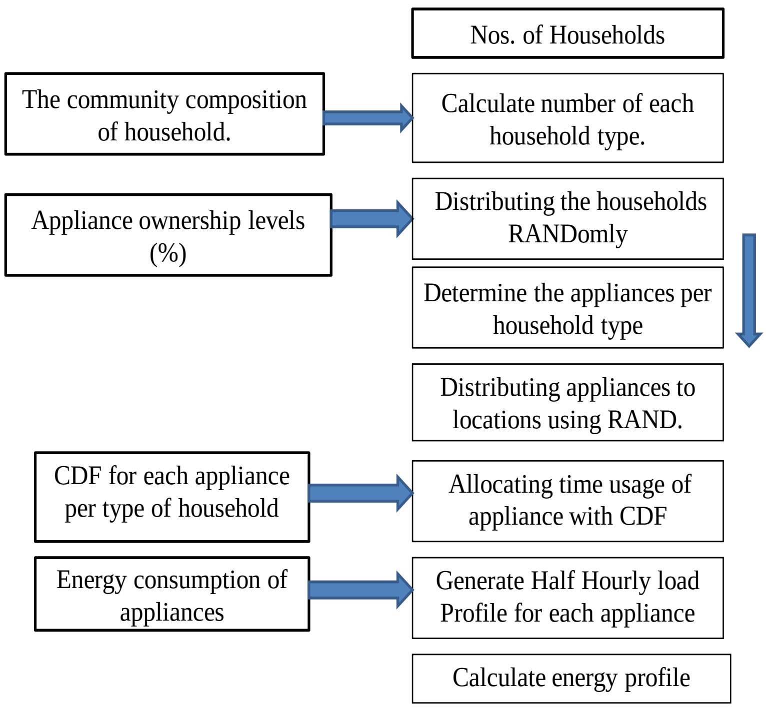

Figure 4.8 Outline of how to produce household load profiles

The household type is then distributed in the community in a random manner reflecting the reality of a community. The appliances for household types are then determined using external data on ownership levels. The appliances are then distributed again in a random manner. The time usage of each appliance is then predicted using the cumulative distributive function that was previously determined by the survey of a similar community; BD7 in Bradford. Finally the energy consumption of each appliance from external data is included so that the total energy consumption can then be computed. The eight loads were generated individually on a daily basis to generate a random half hourly daily load profile for each household type. The summation of the whole community can then be done to determine the community load profile. The total daily electricity demand profile for the community is generated by aggregating the load profiles of the eight scenarios (households).

4.5 Results

Eight daily electricity load profiles were generated separately for each household type on a half hourly basis. As an example of the functioning of the load profile generator, typical half hourly load profiles have been generated for the community that is used in this study. The random fluctuation in daily consumption levels was achieved by using a normally distributed random number.

The electricity load profiles for the eight household scenarios have been generated and then the average values were calculated for each household type and plotted, as shown in Figure 4.9. Note that the random nature implies that results are only particular to the instant. The variation in electricity consumption on a daily level was observed on a half hourly basis.

The peaks in the figure occur around meal times: breakfast time and dinner time are clearly visible. However, it is important to note that all, except scenarios 2 and 6, show the typical small peak in the morning and a significant peak in the evening. The reasons for this are that the two scenarios (2 and 6) are about retired people. Typically they have high energy consumption during the daytime. In scenario 5, a third peak is visible in the afternoon as one of the occupants has a part time job so has to return from work to take care of children returning from school. Scenarios 3, 4, 7 and 8 show similar magnitudes of energy consumption, despite different occupancies.

The aggregate electricity demand for each scenario of the whole community, giving the maximum, average and minimum daily possible values, is shown in Figure 4.10. This was done by running the profile for 23 runs (i.e. random days). The two adults with children household and the two working adults household have the most energy consumption; 28% and 21% of total domestic energy consumption respectively.

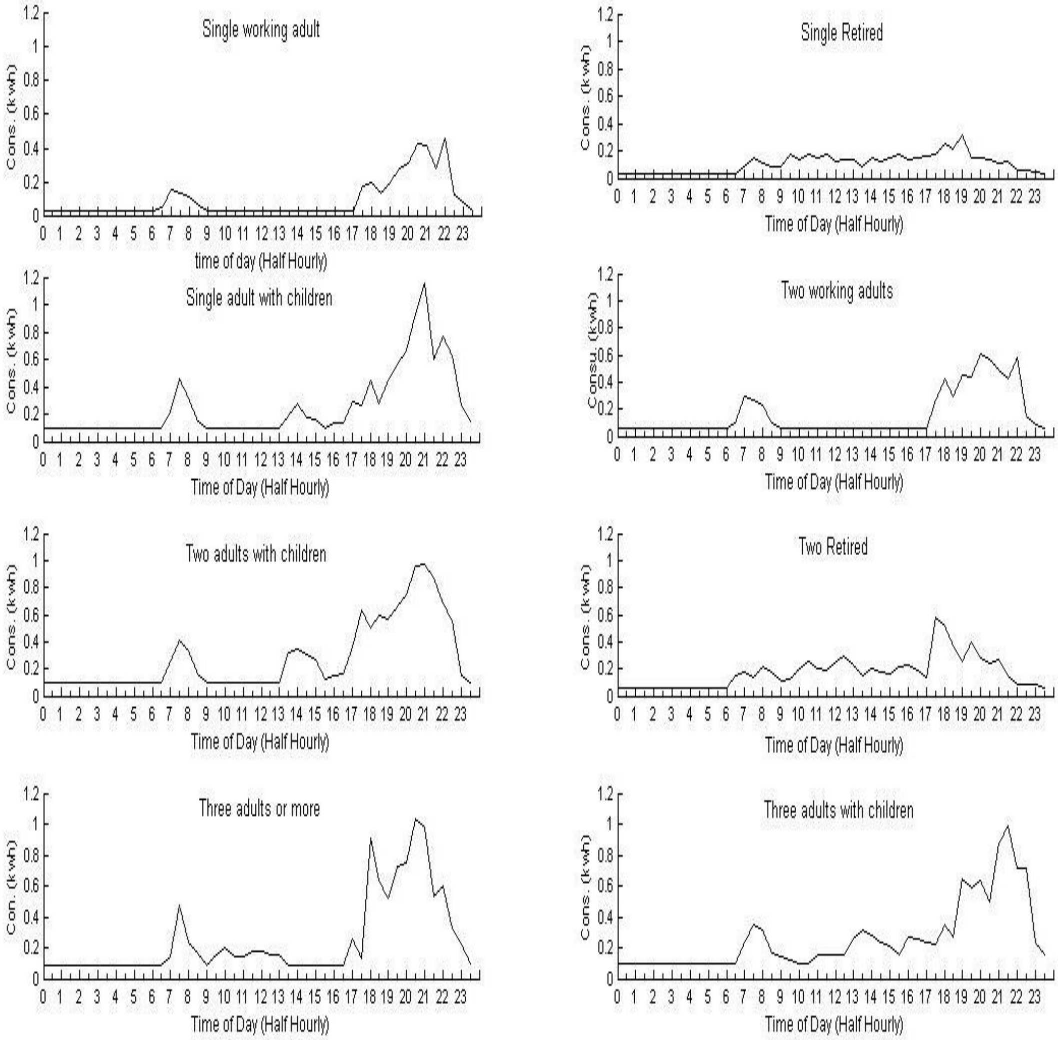

Figure 4.9 Instantaneous half hourly daily consumption for eight scenarios

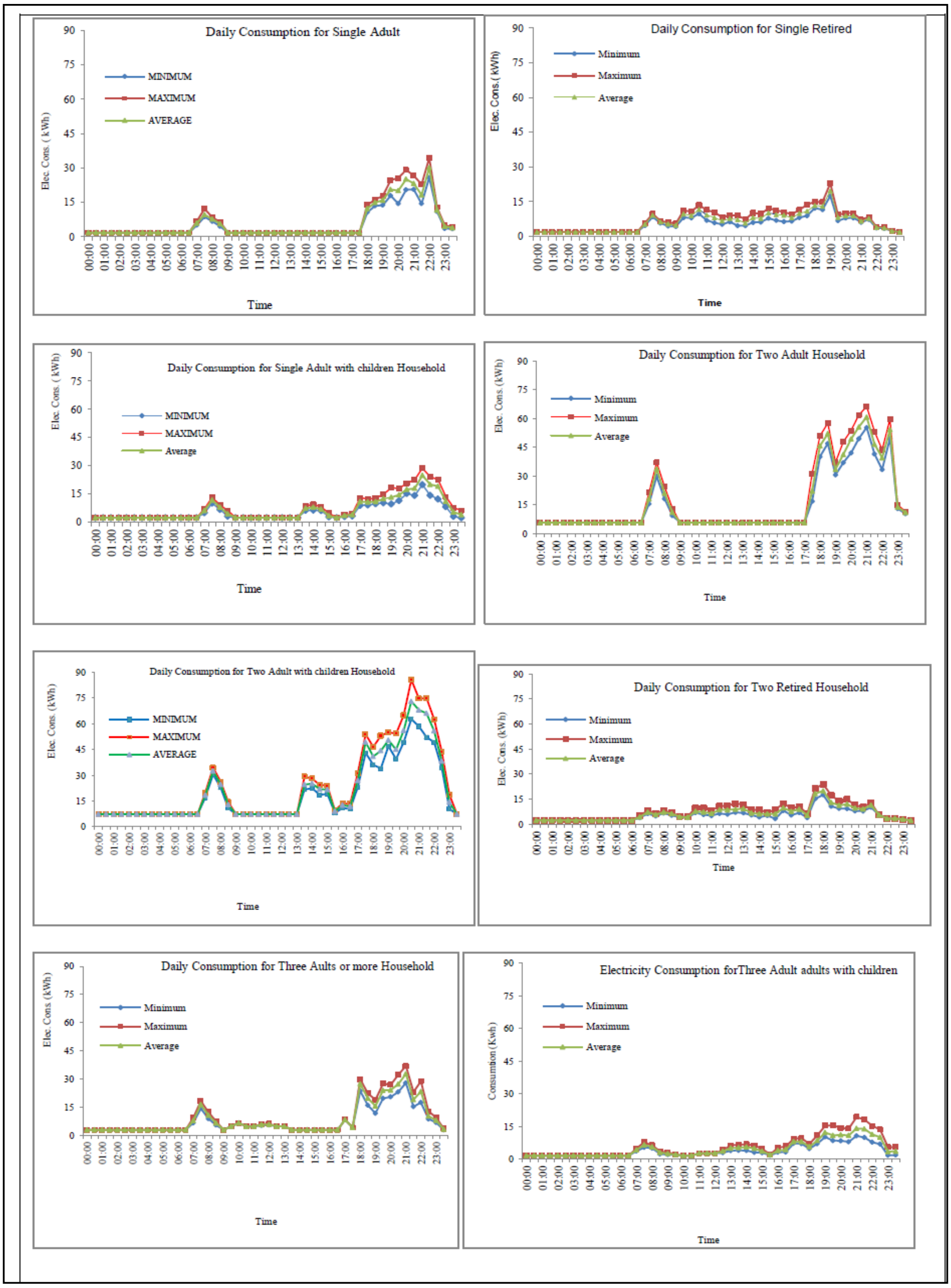

Figure 4.10 Daily maximum, average and minimum consumption in community

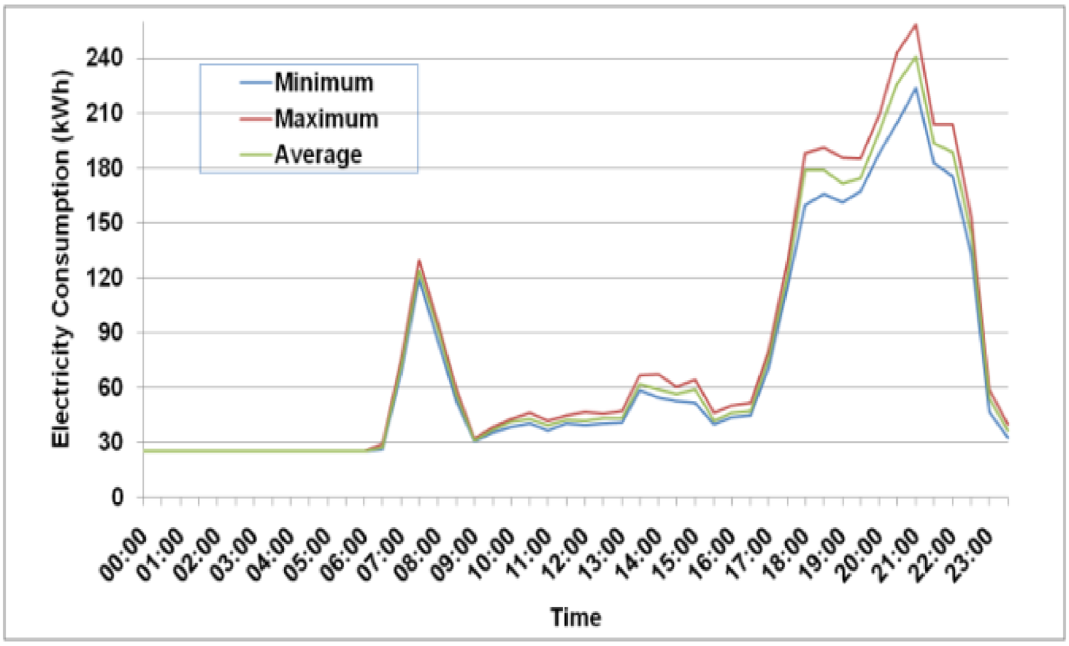

Figure 4.11 Energy consumption profile of the 400 household community

The aggregate daily electricity demand in the particular community of 400 households is shown in Figure 4.11. By observing the generated demand profiles, it is noticeable that the total demand has a peak in the morning, in the afternoon and the highest peak in the evening. The energy usage in the early morning period is very low as would be expected due to few electric appliances being on. The initial peak of about 120 kWh occurs at around 8:00 hrs due to operating such appliances as cookers, kettles and electric showers in order to get ready for starting the day. The energy consumed then remains almost level at 50 kWh with only a slight increase as children return from school. After 17:00hrs, there is a significant increase in consumption (usually the highest peak) as people return home. This remains high until around 21:00 hrs when it starts falling. The maximum and minimum are seen to be significant in the evening period varying by 15% at the highest peak.

The cumulative distribution functions (CDF) enable the generation of the random nature of consumption and can be considered as a good representation of behavior change. Different communities have different behaviors. In order to take into consideration the variation in load consumption various communities may have, different values of cumulative distribution functions (CDF) to describe the usage time of some appliances for different groups of consumers at different communities have been assumed as shown in Figure 4.12.

The effect of variations in CDF on the results of the simulations is shown in Figure 4.13. From the figure it can be seen that the change in cumulative distribution functions (CDF) values has a noticeable effect on the nature of the energy consumption profiles of the community. Therefore, it is possible to improve the database of the tool by obtaining better national representative cumulative distribution functions (CDF) across the country for different groupings and regions, which could be used by local planners

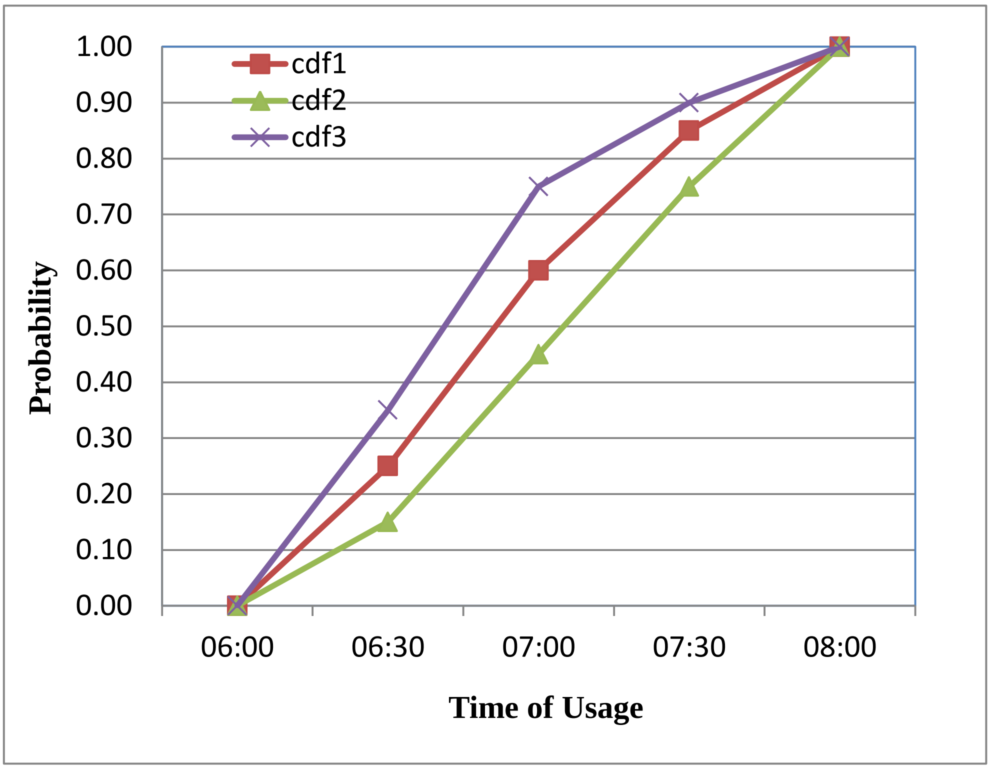

Figure 4.12 Cumulative distribution functions at different values

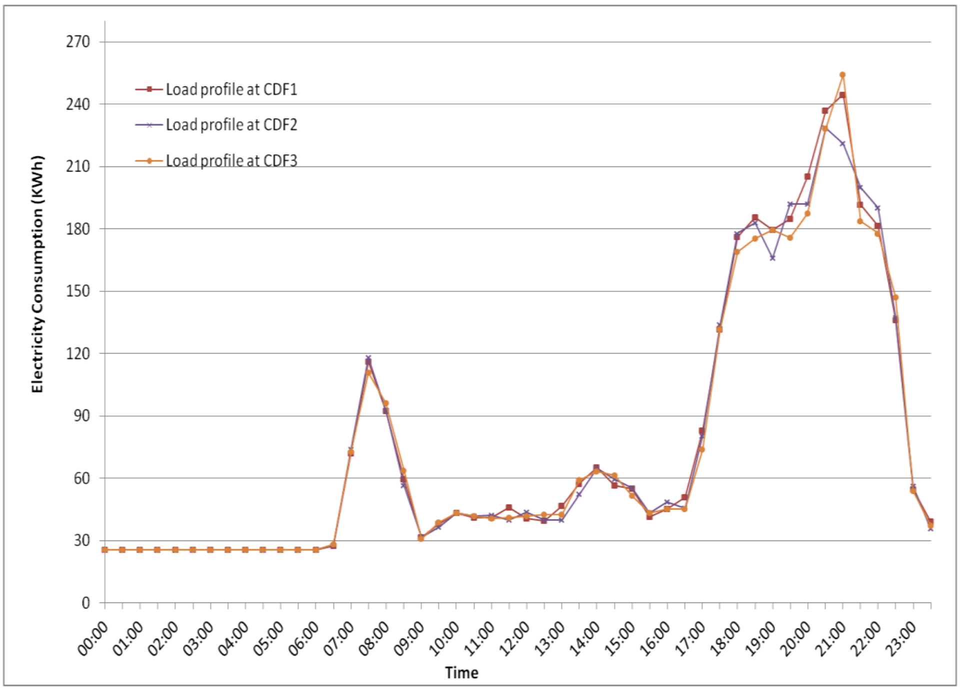

Figure 4.13 Energy consumption profile under different cumulative distribution functions

4.6 Comparison to Measured Data

A measured load profile for a two adults and four children household, as presented in chapter 3 (section 3.3.4) is used for comparison. Figure 4.12 shows the measured data from the household compared with one predicted by the profile generator. The averaged half hourly load profile from the measured data has shown a reasonable agreement compared with the generated load profile for the same household type (i.e., scenario 5; two adults with children household). The average daily electricity consumption from the measured data is about 9 kWh, and about 11 kWh from the generated load profile for the same household type. The profile from monitored data is slightly lower than the generated profile because the cooker was powered by means of gas and the household did not have some appliances such as a dish washer and a tumble dryer.

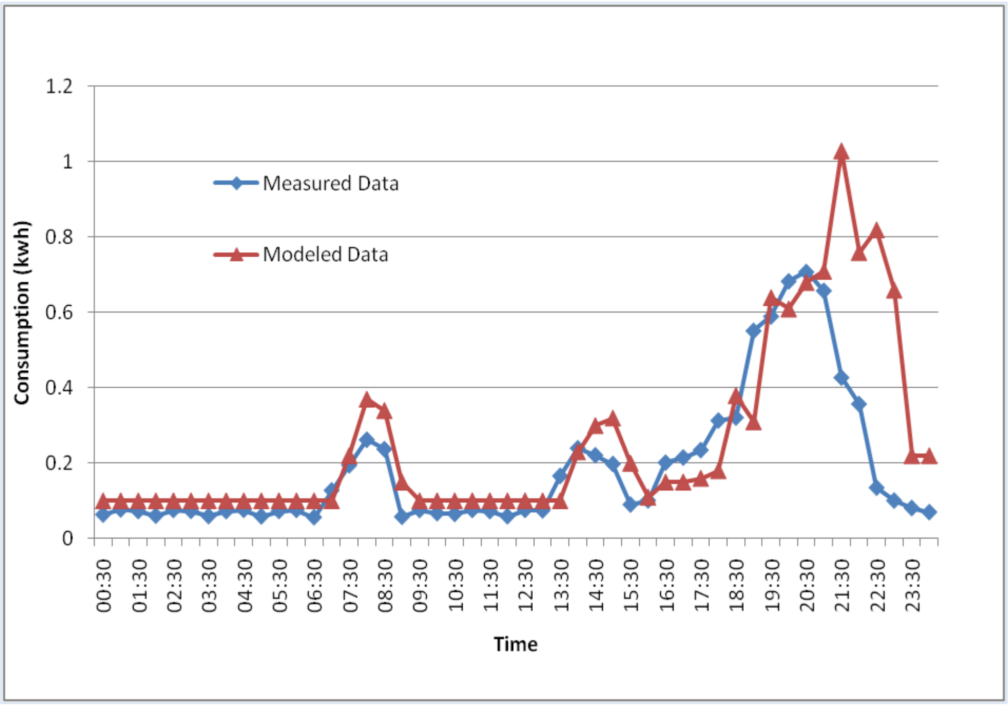

Figure 4.14 Comparison of modeled load profile to measured data

From the figure, it can be seen that the base load of demand occurs overnight and is mainly from cold appliances, continuous appliances and appliances in standby mode. The initial peak occurs between 6:30 hrs and 8:30 hrs. The second peak occurs between 13:30 hrs and 15:30 hrs as one of the occupants returns to take care of the children. Finally, the peak in the evening occurs as the family returns.

The significant difference that occurs after 21:00 hrs indicates that the occupants of the household do not reflect the typical behavior of British households. This is verified to be true as the nationality of the occupants is non-British.

4.7 Discussion

A methodology for generating community load profiles was presented. The load profile can vary significantly between communities due to different housing data, different occupancy types, and different consumer behaviour.

Modelling a small community based on a behavioural understanding of the local community can lead to a better understanding of possible intervention. The procedure used in this thesis was based on a number of key assumptions and data. It was primarily based on a combination of the national statistical data, and a questionnaire survey.

Higher accuracy requires more detailed input data. In this study, the survey was done with only eighty seven participants. With this information, it was possible to profile a similar residential community of four hundred households. For a community that may be different from this (different behavior), we would require a survey to be conducted. Moreover, with updated information, the simulated profiles could be improved.

The methodology presented in this work took into consideration the variation in load dissimilar communities may have, via the use of the cumulative distribution function (CDF). The cumulative distribution function was used to describe the usage time of the appliances for different groups of consumers. It was based on real values of a sample of households' occupancy surveyed data describing when and how occupants are likely to be utilizing their electrical appliances at different times of the day. The simulation is sensitive to the CDF. The change in CDF values has a noticeable effect on the nature of the generated load profiles of the community. The CDF allows us to generate the random values for consumption. The variations in electricity consumption on a daily level were observed on a half hourly basis. These variations indicate that there must be opportunities for behavior change with respect to time of use, so as to result in less peak demand.

To enable the tool to be useable for different communities, the database of the tool could be improved by generating national representative cumulative distribution functions (CDF) across the country for different groupings and regions, which could be used by local planners.

The results showed which category of household contributes most to the energy usage peaks. It is possible therefore to focus energy conservation on those households first rather than the whole community, which may be too costly. The variations in the daily usage between maximum and minimum indicate that there must be opportunities for behavior change with respect to time of use so as to result in less peak demand. The tool does not consider the variation in load from weekdays to weekend to avoid complexity and this should be considered in future work.

4.8 Conclusion

This chapter can be concluded as follows:

- A new methodology to predict electricity energy scenarios for small residential local communities has been presented to help local planners decide on measures such as embedding renewable energy and demand management.
- The inputs are based on a limited set of statistical data of household types, and of ownership levels, both of which are available in the public domain.
- The scenarios are made relevant to the communities being investigated by

carrying out a straightforward survey of consumer behaviour in similar communities.

- The differences between eight types of households show that occupancy has a significant impact on energy consumed. This is something local planners could modify, if their community's households differ from national types, in order to help plan for their communities.
- The result was compared with measurements of a single household, and shows reasonable agreement.
- The results of the generated load profiles have been used to evaluate the incentives currently available to consumers for shifting load.
- The results of the generated load profiles have been used to study measures that could be used to reduce energy consumption. The resulting generated load profiles are being used to assess the impacts of time of use (TOU) tariff plans (economy 7) on domestic consumer behaviour and energy savings.

Chapter 5

Investigation of Tariff Initiatives for Peak Load Shaving at Domestic Level

This chapter presents and discusses an investigation of the use of economy 7 tariffs as an incentive to generate demand response, and shows the impact of these tariffs on consumer behaviour in UK domestic buildings, using the results presented in Chapter 4.

5.1 Background

Rising electricity demand and worries over a future lack of resources make energy management tools such as peak load reduction or load shifting a valuable method for maintaining a stable and efficient network. Domestic load balancing is a major concern for several countries, particularly where the demand is close to the available generation capacity. This is represented in the deregulated market by higher pricing during peak periods. The results of the generated half hourly domestic electricity load profile presented in Chapter 4 are used to evaluate the incentives currently available to consumers for shifting load. With the generated electricity demand profile, consumers' bills at both standard tariffs and time of use tariff plans have been calculated. This chapter discusses some aspects of electricity markets from the perspective of the demand side. It also outlines the tools and techniques that should be developed to help consumers take advantage of the opportunities offered by competitive markets. An optimization model of electricity tariffs using load shifting to maximize the consumers' gain by shifting to an economy 7 (TOU) tariff rather than a standard tariff, was proposed.

5.2 Introduction

Peak demand is a key issue in power supply systems when demand goes over the available capacity. Continuous growth in peak load raises the possibility of power failure, and raises the marginal cost of supply. In the UK the domestic sector accounts for about one third of total electricity use. It contributes the largest peak demand, particularly in the winter season, which has consequences for the power infrastructure.

Under competitive electricity market conditions, if a reasonable electricity tariff for consumers is determined, consumers could be encouraged to modify the style of their consumption in response to financial incentives. Consequently we can achieve the objective of making the load more level and recover the stability and efficiency of the power system. Demand response (DR), is defined as the changes in electricity usage by end use consumers from their usual usage patterns in response to changes of the electricity price over time. Demand response relates to the fact that the behaviour of occupants in their own homes results in significant changes in electricity load that are often highly correlated and thus have a considerable impact on the electricity supply system both locally and system wide.

Time of use tariff (TOU) is one of the significant tools of demand side management (DSM) which encourage consumers to adjust their consumption during the high demand periods [79]. Time varying tariffs offer smart off peak rates, but relatively high peak rates. TOU tariffs for domestic consumers were first begun in 1965 and led to an exceptionally significant growth in electric storage water heaters and a resultant growth in off-peak use including the Economy 7 tariff scheme in the UK [80].

Economy 7 is a cheaper night time electricity tariff which normally operates from midnight where seven hours of low tariff electricity at night but slightly more expensive tariff throughout the day. In the UK, this is most effective for those customers that use electric heating. This is because of the high load for heating. However, the majority of houses in the UK now have gas central heating systems. The incentives for load shifting of the peak are therefore limited.

5.3 Demand Side Management

Demand Side Management (DSM) programmes began modestly in the 1970's in response to the impacts of oil crises on the electricity utility industry. These oil crises led to a rapid increase in energy price, increased cost of power generation and subsequently higher electricity costs [81, 82].

Due to technological and economic developments energy demand has gradually increased. The old way to assure this increasing demand was to increase supply capacity by constructing more power generation plants, which was formally called supply side management (SSM) [83]. However, due to limited energy resources, a deteriorating environment, and unfavourable demand profiles another strategy to meet demand needed to be found. It soon became clear that the SSM approach was inappropriate for sustainable growth either from an economic or an environmental point of view. Nowadays, DSM has become part of the application of integrated resource planning (IRP) and refers to a series of approaches and options to help utilities maintain a balance of electric supply and demand under uncertain conditions [81]. Currently, facing the prevailing change in electricity market structure, DSM implementation has come into a new era and is leading changes in the design of the restructured utility market. The DSM programmes have focused on how to manage the consumption pattern of electrical appliances by minimizing the negative impacts on consumers [84]. Demand Side Management (DSM) vs. supply side management (SSM) is described in Table 5.1.

Table 5.1 Demand side management Vs. supply side management

DSM	SSM
After the consumer meter	Before the consumer meter
- Reduce power - Shift time of use - No reduction in service quality	- Increase generation capacity - Improve generation efficiency - Reduce transmission and distribution losses

5.3.1 Definition and Objectives of Demand Side Management

The concept of Demand-Side Management (DSM) was initiated by the utility industry primarily for changing the timing and level of electricity demand, i.e., the shape of electricity loads, among their customers.

Demand Side Management (DSM) is a technique used by utilities to control the loads in order to achieve a better overall network performance and to obtain a better match between the available supply and the consumer demand, so that their connection to the grid is scheduled according to the availability or cost of power. In other words, DSM is the implementation of those measures that help the consumers to use electricity more efficiently in order that power can be produced in an optimal way [84-86].

5.3.2 Approaches to Demand Side Management

One approach in residential load management is direct load control (DLC). Direct load control allows a utility to turn on or off particular appliances at the time of peak demand periods by direct control. This kind of load control contains encroachment on the consumer's right to use his electricity supply as he needs. However, users' privacy may be a barrier when load control is utilised in residential situations. An alternative is dynamic pricing, which is designed to reduce system costs for utilities and bring down customer bills. Dynamic pricing programmes can be targeted at many kinds of customers, from the residential consumer through to the commercial consumer and the industrial consumer. The electric utility company is most often responsible for programme design, implementation, and evaluation and monitoring. The implementation of new metering and billing systems and sometimes the installation of end-use controlling equipment are involved [91]. With dynamic pricing, users could be encouraged to manage their load. In this regard, time-of-use pricing (TOU), critical peak pricing and real time pricing are among the most popular options [80].

- Time-of-Use Pricing (TOU): Electricity prices are designed higher in time of peak hours and lower in off-peak time, typically not changing more often than twice a year. Prices charged for energy used during these periods are well-known to consumers in advance, enabling them to change their consumption in response to prices and therefore cope their energy costs by shifting load to a lower cost time or reducing their use overall.

- Critical Peak Pricing (CPP): This rate design is based on a time of use scheme (TOU) combined with an additional penalty charged over the standard peak time of use price for consumption during these hours when electricity is costly or system conditions are critical. CPP is only used on a limited number of days each year [88, 89]. Although CPP represents an improvement to time of use (TOU), it has the drawback that the penalty charges are set in advance and the numbers of occasions on which they can be applied are limited. Critical peak pricing needs a better level of metering than time of use rates which needs only on-peak and off-peak usage measurements, whereas CPP must be capable of hourly measurements of load. Moreover it also needs further communications equipment in order to inform customers of the time of critical hours.

- Real Time Pricing (RTP): This type of pricing is based on the scheme that the electricity price should always reflect the current market situation. Under a real-time pricing, the electricity prices vary hourly or sub-hourly all year long, for all or some of a customer's load.

5.3.3 Implementation of DSM

The key components of DSM are load control, load management, remote metering and billing automation. Load control and management is used to analyse situations such as users' electricity consumption, electricity prices, weather and heating characteristics in buildings in order to determine the optimal operation and load control scheme and also guide the consumers to shift load and flat load curves with reasonable pricing structures. The main categories in this DSM activity are: [79]

- Energy reduction programs (ERP): reducing demand through more efficient processes, building or equipment;

- Load management programs (LMP): changing the load pattern and encouraging less demand at peak times and peak rates.

Remote metering and billing automation allow the generation of reports and curves of electricity prices automatically by obtaining meter data from remote consumers and transmitting it to the control centre.

Load management programmes aim to manage the power on the demand side using various technical and economic measures to reshape the load curve into the objective curve to enable the supply system to meet the demand at all times in a cost-effective manner [88]. The load on the system is always changing with time and never remains constant, so that utility providers must keep an eye on the maximum load and average load of their systems. Load management programmes basically optimize the loads to improve the system load. The load factor is the ratio of the average load to the maximum load within a certain period.

$$Load\ factor = \frac{\text{average load}}{\text{maximum load}} \tag{5.1}$$

The ideal value for the load factor is 1, which indicates that the average load is equal to the maximum load. However, practically this is impossible and it is always less than one (< 1.0). The lower this load factor, the greater the fluctuations within the demand profile. This results in increased capacity and cost for the operation of the supply side. Therefore measures need to be implemented which improve the load factor. Load management is a suitable way of increasing the load factor, which is the process of scheduling the loads, to reduce the electrical energy consumption or the peak demand at a given time. Figure 5.1 illustrates different load shape objectives of demand side management programs. These include: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape:

- Peak clipping: denotes to the reduction of utility loads during peak demand periods. This can reduce the need to operate at the most expensive unit and defer the need for future capacity additions to decrease the utility's cost of service. The net effect is a reduction in both peak demand and total energy consumption. The method usually used for peak clipping is by direct utility control of consumer appliances or end-use equipment.
- Valley filling: encourage consumers to use energy when the energy price is low. This is the process of making an energy production and delivery system more efficient by encouraging additional energy use during periods of lowest system demand.
- Load shifting: involves shifting load from on-peak to off-peak periods. The net outcome is the reduction in peak demand, but no change in total energy consumption. Typical methods used for load shifting are the time-of-use (TOU) rates and/or the use of storage devices
- Strategic conservation: encourage consumers to use efficient energy such as renewable energy and energy efficient appliances to reduce energy use in order to lessen average fuel cost and reschedule the need for future utility capacity additions.
- Strategic load growth: encourage consumers to use electro technologies instead of inefficient appliances such as fossil-fuel equipment. This can decrease the average cost of service by distributing fixed costs over a larger base of energy sales and benefits all customers.

- Flexible load shape: use programs such as demand subscription services and priority service pricing which alter energy consumption. Utilities can realize both operating and future fixed costs by allowing dispatchers the flexibility to reduce or postpone demand for selected customers [83].

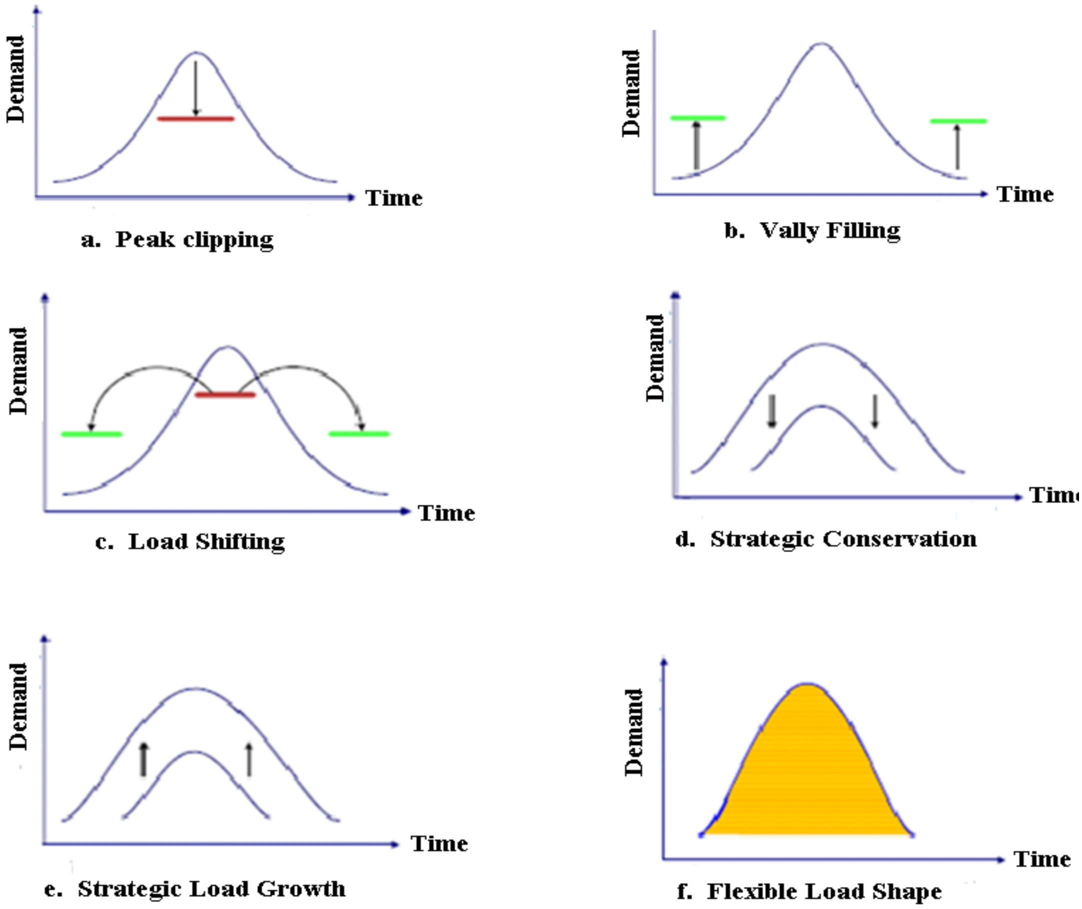

Figure 5.1 Demand side management load shape curves [83]

5.4 Electricity Tariffs Structure

As residential energy markets open to competition, consumers can choose from a range of tariffs offered by different suppliers. Currently in the UK, most domestic consumers, who have no electric heating, have slight or no incentive to shift their usage away from peak periods as they are charged at standard electricity tariffs for their consumption regardless of time of use. The standard tariff consists of a standing charge tariff, a Tier 1 charge for an agreed amount of usage, and a Tier 2 charge for the remainder. A standing charge is a fixed amount the consumers pay daily to their electricity supplier. It's a little like a connection fee and the consumers also pay for the electricity they actually use. It is used to cover the energy suppliers' costs such as meter reading, maintenance and the cost of keeping the consumer connected to the network.

The economy 7 tariff is a cheaper night time electricity tariff which normally operates from around midnight for seven hours. To shift more energy consumption into the night, some main appliances such as, washing machines, tumble dryers or dishwashers might be configured to run during the night period tariff i.e. early morning. To examine the consumer's behaviour in response to the tariff changes, consumers' quarterly electricity bills under different standard tariff schemes offered by five suppliers in the UK, were calculated. Table 5.2 shows the actual electricity standard tariff plans offered by five suppliers in 2010 in the UK [90].

Table 5.2 Standard tariffs (including VAT) offered by different suppliers

Supplier	**Standing Charge**	**Tier 1**	**Tier 2 (for the rest)**
1	-	14.91p/ kWh for the first 720 KWh	13.90 p / kWh
2	8.4210 p/day	11.885p/ kWh	-
3	-	19.91p /kWh for the first 900 KWh	9.84 p/ KWh
4	-	23.538p / kWh For the first 500 kWh	9.172 p/ kWh
5	13.301 p/ day	10.2250 p / kWh	-

The Tier 1 day rate will apply to a block of 1000 kWh or 720 kWh each year (e.g. for an electricity bill covering three months the first 247 kWh will be charged at the Tier 1 rate, all extra day kWh will be charged at the Tier 2 rate). Night consumption will be supplied for a total of 7 hours between 11pm and 8am (actual times set by the local network operator) and these will be charged at the night kWh rate. Table 5.3 shows actual electricity economy 7 plans offered by two suppliers in 2010 in the UK [90].

Table 5.3 Economy 7 electricity tariffs rates (including VAT)

Brand	**Supplier**	
Supplier	**X**	**Y**
Tier 1 rate	23. 80p/ kWh for the first 1000 kWh	22.134p/kWh for the first 720 kWh
Tier 2 rate	11.21p/kWh for the remainder	13.288p/kWh for the remainder
Night rate	5.03p per kWh	4.63p per kWh

5.5 Analysis of Household Electricity Consumption

To obtain a better understanding of the effect of different tariff schemes on consumer behaviour, half hourly load profiles for different types of households as presented in Chapter 4 is used.

An analysis of domestic electricity consumption was carried out to determine if UK households are responsive to the economy 7 tariff scheme. These household are assumed to all have gas central heating.

5.5.1 Load Profile Data Characteristics

A consumer's consumption of electricity is influenced by the number, type and time of usage of electrical appliances. Households do not have to reduce their consumption to benefit from low tariff rates at off peak periods. By shifting their electricity consumption to lower rate periods, which means they use electricity in off peak periods, consumers can save on their electricity bill even if they do not reduce their consumption.

Household actions needing electricity include food preparation, using electronic apparatus, running appliances etc. Of these activities, utilizing wet appliances (e.g. tumble dryers, washing machines and dishwashers) outside of peak periods is likely to result in the least disruption to households and personal lifestyles. The percentage share of electricity consumption by household domestic appliances is shown in Figure 5.2. The largest share was for the wet appliances which accounted for 19 percent of the total amount of electricity consumed, followed by brown appliances (18 percent), cooling appliances (17 percent), miscellaneous (16 percent), and lighting (13 percent). As such, it is feasible to shift the wet appliances usage to different time periods.

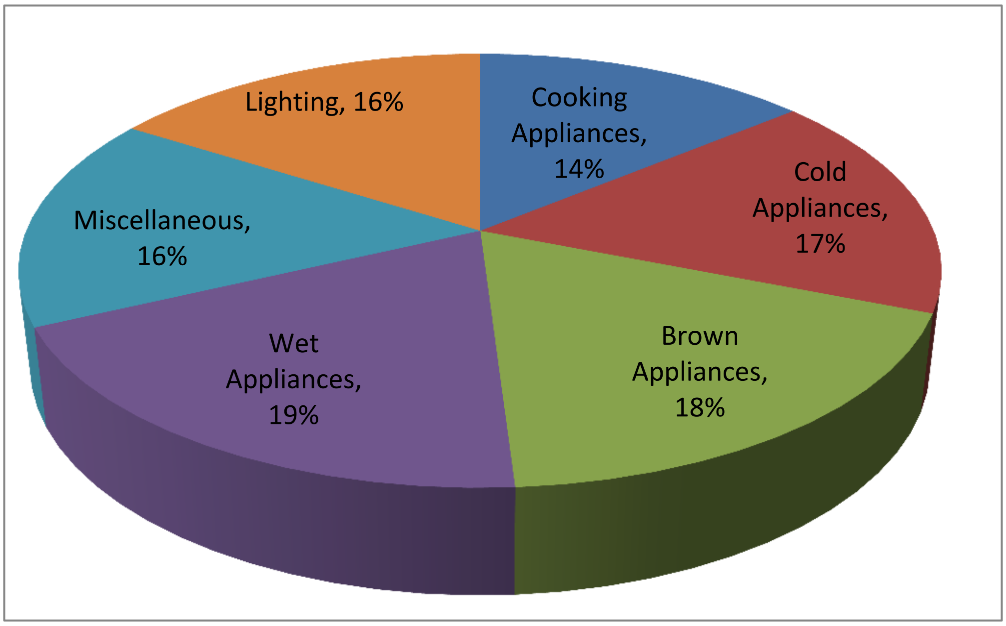

Figure 5.2 Electricity consumption by households' domestic appliances

5.5.2 Bill Calculations

The generated household electricity consumption data presented in Chapter 4 has been manipulated in two ways to help determine the likely change in the electricity bill and shift in electricity use in response to economy 7 tariff schemes. The two ways are described below:

- Will the households gain naturally from the adoption of economy 7 tariff rates? That is, are there any households that are expected to save on their electricity bills, given their electricity use patterns without the adoption of economy 7 tariff rates (i.e. under standard tariff schemes). A comparison between different consumers' bills under standard tariffs offered by five suppliers has been made in order for consumers to understand more about standard tariffs before choosing their suppliers. The general equation to calculate the quarterly consumer's bill under the standard tariff is:

$$S = Q_F . x_1 + Q_2 . \boldsymbol{x_2} \tag{5.2}$$

where:

S is the electricity bill under standard tariff, Q_F is a fixed consumers' energy use in lower tier (i.e., the first 1000 kWh will be charged at the Tier 1 rate), Q_2 is all extra consumed kWh, x_1 is tier 1 rate (£/kWh), and x_2 is tier 2 rate (£/kWh).

The general equation to calculate the quarterly consumer's bill under economy 7 tariff is:

$$E = Q_F . x_3 + Q_4 . x_4 + Q_N . x_5 \tag{5.3}$$

where:

E is the electricity bill under economy 7 tariff.

$Q_F = \text{Tier 1 fixed usage at tier 1 (kWh) under Economy7 tariff.}$

Q_N =elec. consumed during night period (kWh) under Economy7 tariff.

$Q_4 = \text{Tier 2 extra usage above tier 1 (kWh) under Economy7 tariff.}$

$x_3 = \text{Tier 1 rate (p/kWh), under Economy7 tariff.}$

$x_4 = \text{Tier 2 rate (p/kWh), under Economy7 tariff.}$

$x_5 = \text{Night rate (p/kWh), under Economy7 tariff.}$

Under the same energy usage: $Q_2 = Q_4 + Q_N$

The daily percentage of electricity consumed during the Tier 1, Tier 2 and night periods was calculated for each household type and for the whole community prior to the adoption of the economy 7 tariff.

The difference between the tiered costs and the expected economy 7 costs $(E - S)$ was calculated for each household. Positive differences indicate that the expected economy 7 costs would be greater than the actual tiered costs, and thus indicates that the household is not expected to benefit naturally under the new economy 7 rate scheme. Similarly, negative differences indicate that the expected economy 7 costs would be less than the actual tiered costs, and thus indicates that the household would be expected to benefit naturally under an economy 7 rate.

- Do the households shift the time when they consume electricity upon the adoption of the economy 7 tariff rate? That is, do the households shift the usage of appliances such as washing machines, tumble dryers, kettles and irons to run a bit earlier in the morning.

Table 5.4 Electricity consumption ratio during periods

	Scenarios							
	1	2	3	4	5	6	7	8
No. of households	60	60	24	96	76	36	32	16
	Electricity consumption (%)							
Night Period	15	14	17	18	16	16	18	15
Tier 1 (limit)	52	50	19	31	19	30	20	18
Tier 2 Period	33	36	64	51	65	54	62	67

Each of the households has similar average percentages of electricity consumed during night periods, as shown in Table 5.4. The average household proportion of electricity consumed during night periods ranged from 14% -18% between the households. Scenarios 4 and 7 have the highest proportion of electricity consumed during night periods.

5.5.2.1 Natural Benefits (without load shifting)

The calculation performed was intended to determine if households would benefit naturally from the adoption of economy 7 tariffs. To answer this question, a comparison between quarterly bills from each household type under both the standard tiered rates offered by five suppliers and economy 7 rates was performed, as shown in Figure 5.3. From the figure, it can be seen that the households have an average quarterly electricity bill associated with tiered tariff (standard) in the range of £56 to £167. The average quarterly electricity bill of these households associated with the economy 7 tariff ranged from £76 to £165.

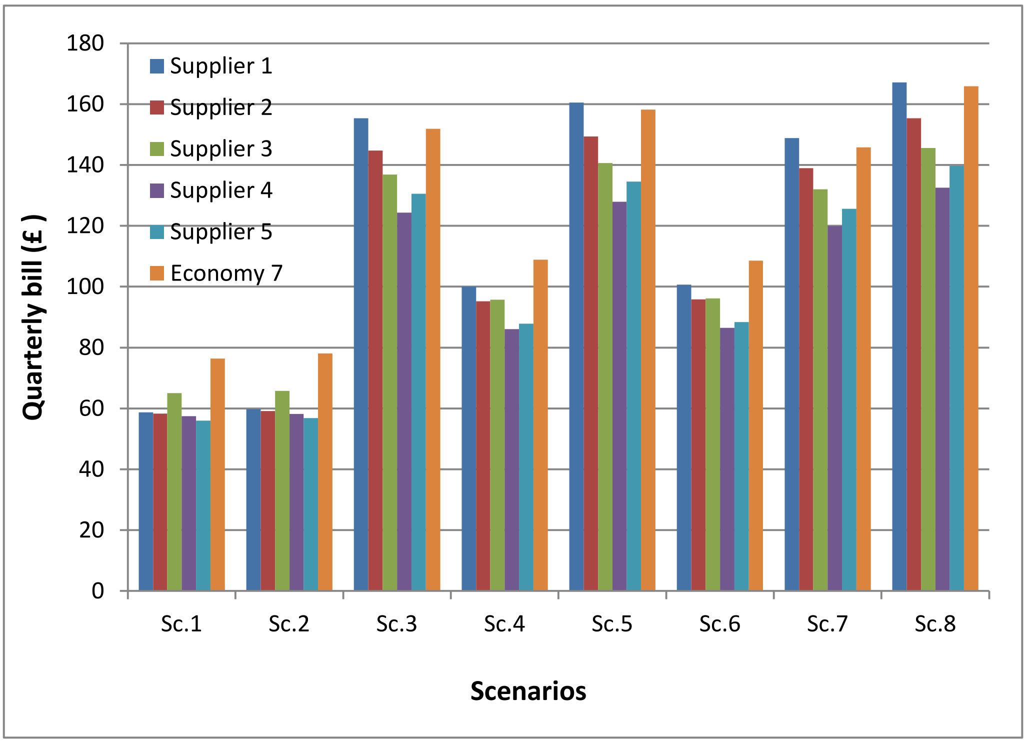

Figure 5.3 Quarterly consumers' bills using different standard tariffs & economy 7 tariff, for the eight scenarios

The single adult and single retired households have the lowest quarterly electricity bill associated with standard and economy 7 tariffs, while the two adults with children and three adults or more with children households have the highest quarterly electricity bills associated with standard and economy 7 tariffs.

The results denote that none of the eight scenarios would benefit naturally from the economy 7 tariff. Also, from Figure 5.3, it is clear that some consumers (scenarios 3, 5, 7 & 8) will benefit naturally from the adoption of economy 7 tariff rates if they are on standard tariffs offered by the first supplier. This is because the standard tariff is different at Tier 2, making it more costly for users. If Tier 2 rates of the standard rate were higher; it would force some customers to shift to economy 7. This is effectively what would be required as Tier 2 represents the additional usage of customers, and Tier 1 the fixed bill.

5.5.2.2 Load Shifting

If the load is now shifted from Tier 2 to night time, there could be possible savings. Using a standard tariff scheme as baseline, and two economy 7 tariffs, options 1 and 2 described below explore this idea and the results are illustrated in Figures 5.4 and 5.5.

As shown from the figures, the percentages of possible savings under the standard tariff and the expected economy 7 tariff were calculated for each household type (scenario).

Standard tariff: (supplier 3)

Tier 1 rate: 19.91p (inc. VAT) per kWh for the first 900 kWh

Tier 2 rate 9.84p (inc. VAT) per kWh for the remaining usage

Option 1: Economy 7 tariff: (supplier X)

Tier 1 rate**:** 23. 80p (inc. VAT) per kWh for the first 1000 kWh

Tier 2 rate: 11.21p (inc. VAT) per kWh for the remaining usage

Night Rate: 5.03p (inc. VAT) per kWh.

Figures 5.4 and 5.5 show for each scenario, the savings compared with the standard tariff (negative indicates loss). The graphs indicate that in option 1, a minimum of 25% load shift is required. However, for option 2, a load shift of 15% is sufficient for some households to benefit.

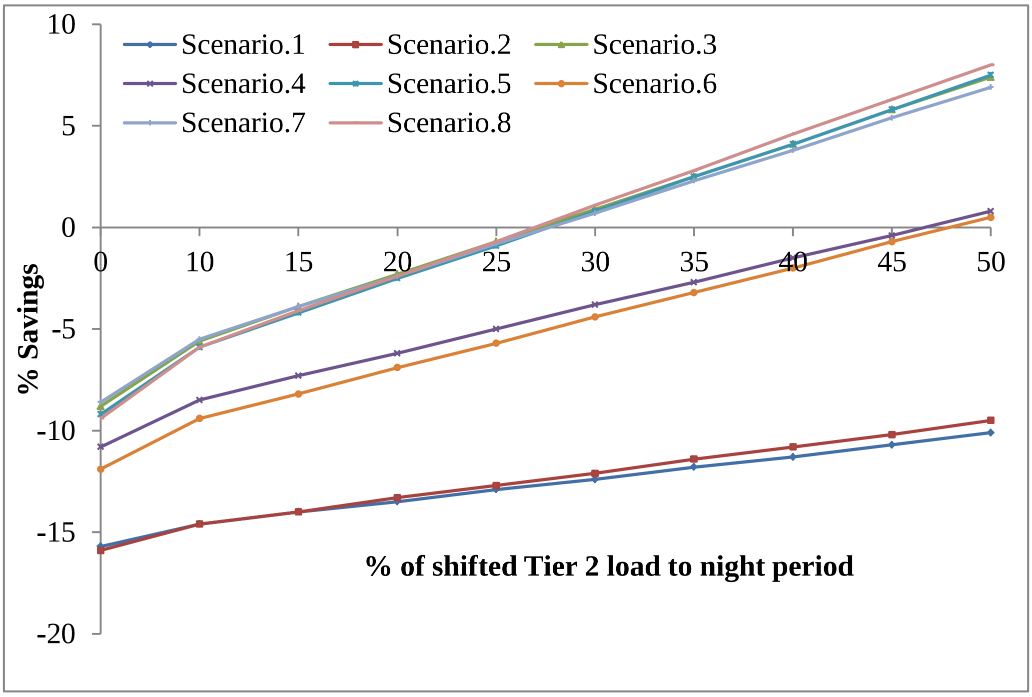

Figure 5.4 Savings with option 1 pricing

Option 2: Economy 7 tariff**:** (supplier Y)

Tier 1 Rate**:** 22.134p (inc. VAT) per kWh for the first 720 kWh.

Tier 2 Rate: 13.288p (inc. VAT) per kWh for remainder.

Night Rate: 4.63p (inc. VAT) per kWh.

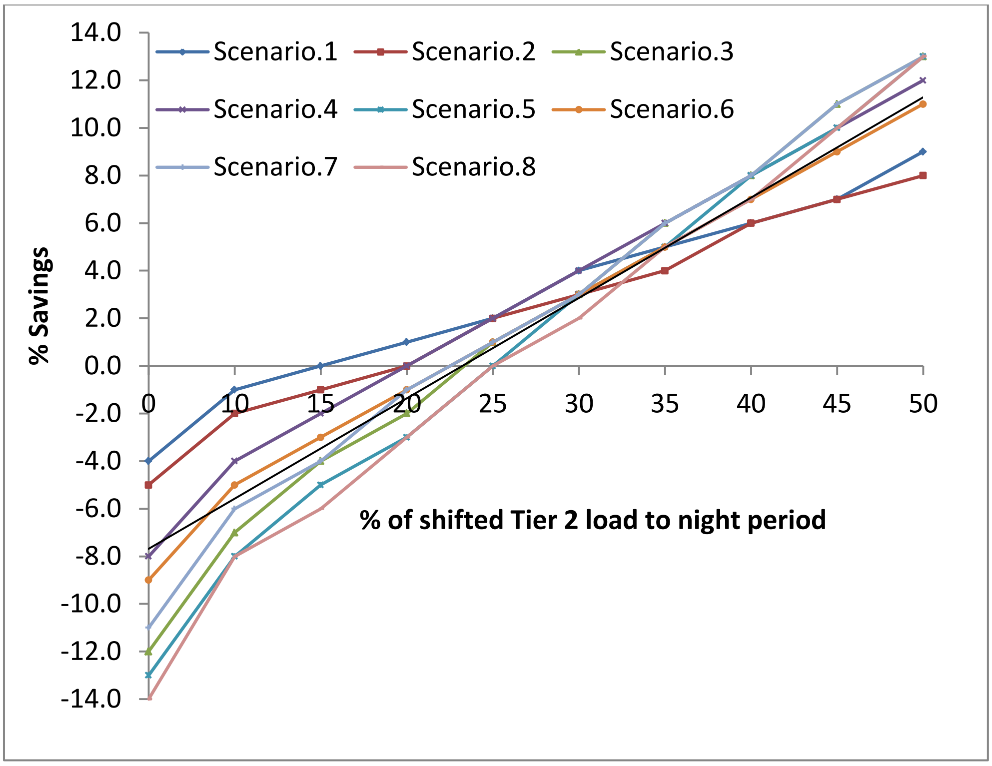

Figure 5.5 Savings with option 2 pricing

5.5.2.3 Practical Adoption of Economy 7 Tariff (option 2)

The previous calculations were all done by numerically shifting the load. However, in practice, it is the usage of appliances that has to be shifted by behavior. In this section we examine shifting the usage of appliances such as washing machines, tumble dryers, kettles and irons to run a bit earlier in the morning (before 8am). Table 5.5 shows the shifts and gains made with various changes in appliance usage. The table shows that with a significant amount of change in behaviour from the consumer, the total amount of load shift was only around 23%. At this level only a few consumers get a slight benefit. The reason for this is that most of the bill is actually made of Tier 1 & Tier 2, and the ratios are different, as shown in Figure 5.5. The change must still be made at Tier 1 and 2 for there to be a shift. This can be done by conventional optimization techniques.

Table 5.5 Percentage savings in consumers' bills using economy 7 tariff (option 2) compared to standard tariff for load shifting of (i) Washing Machine (W/M) (ii)W/M + Dryer (iii)W/M + Dryer + Iron (iv)W/M + Dryer + Iron + 0.3 of Kettle's load (v)W/M + Dryer + Iron + 0.3 Kettle + Vac. Cleaner

Load shift	**i**	**ii**	**iii**	**iv**	**v**
% of Tier 2 load shifted to night	9	17	20	21	23
Scenarios	**% Savings**				
1	-1.3	0.2	1.2	1.5	2.2
2	-2.5	-1.2	0.6	0.9	1.8
3	-7.5	-2.8	-1.3	-1	0.1
4	-5	-2.3	-0.9	-0.8	0
5	-9.3	-4.9	-2.9	-2.7	-1.4
6	-5.9	-3.8	-2.6	-2.2	-2
7	-6.5	-2.6	-1.1	-0.2	0.7
8	-9.5	-5	-3.6	-2.8	-2.3

5.6 Utility Load Facing

Figures 5.6 and 5.7 show the typical electricity load profiles for the selected scenarios and the whole community respectively for load shifting using scheme (iv). It can be seen that a percentage of the daily load in the peak hours can be shifted to early morning hours.

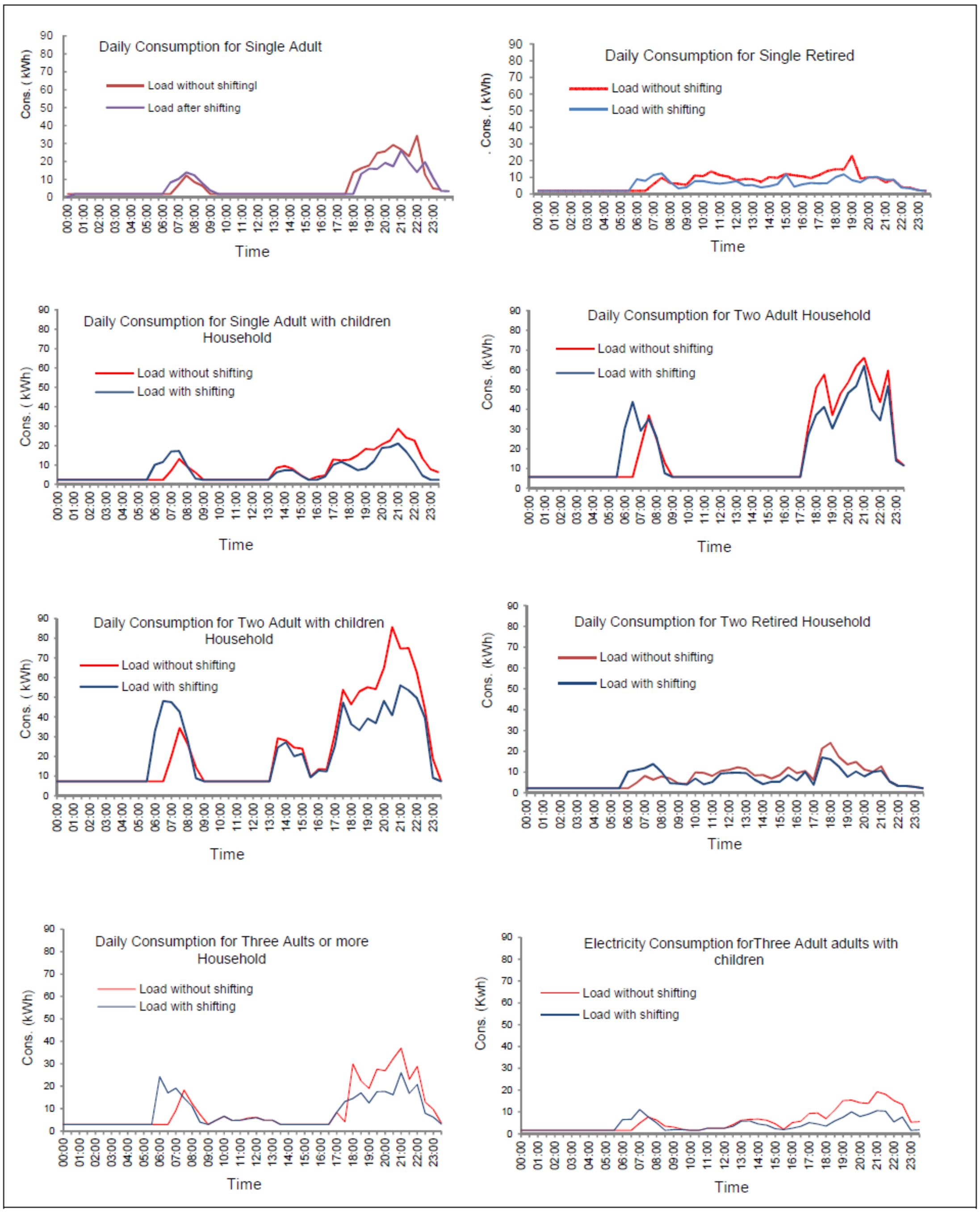

Figure 5.6 Comparison of normal electricity consumption profile with load shift

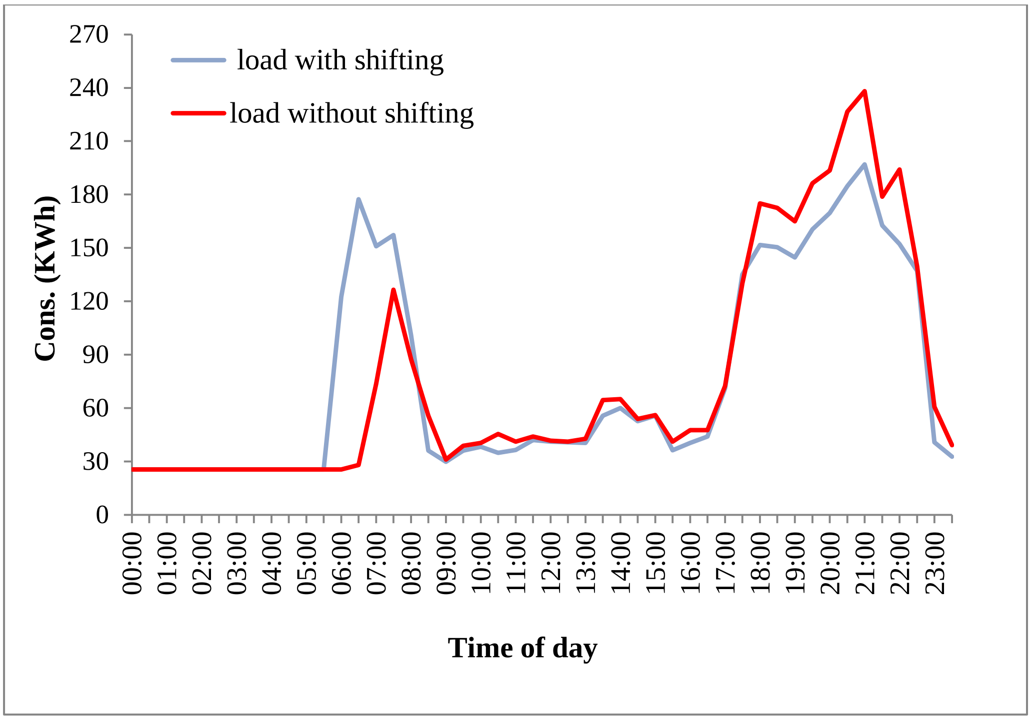

Figure 5.7 Comparison of normal electricity consumption profile of the 400 household community with load shift to night hours

The benefit to the utility would be dependent on what rates they actually purchase the electricity at. If the cost is significant, then there would be an incentive to invest in trying to change the behaviour of the consumers. However, the focus of any attempt should be on the type of households where the benefit would be significant. Figure 5.8 shows the amount of energy shifted by type of household. It can be seen that the two adults, and the two adults with children represent about half the energy shifted. As such, the utility could target marketing literature, and any incentives on those consumers.

There is however, the issue that utilities may not be interested in changing national tariffs. If so, it may be possible for a local community company or organisation, newly entering the market, to make such changes.

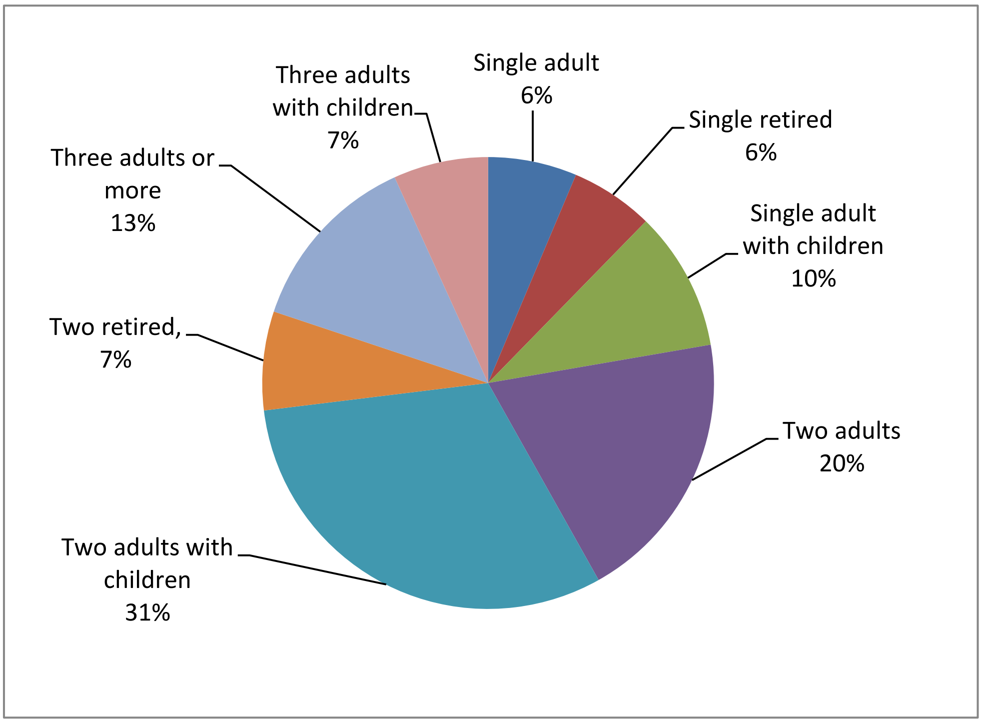

Figure 5.8 Proportion of load shifted in kWh for scenarios (scheme iv)

5.7 Optimization of Electricity Tariff

For domestic electricity tariffs to be effective, it is essential that the tariffs offered are designed in such a way as to adequately motivate consumers to change their electricity usage behaviour. Load balancing is a major concern, particularly where the demand is close to the available generation capacity. Demand is largely uncontrollable and varies with time of day and season (there have been insufficient incentives for demand to become responsive). This is represented in the deregulated market by higher pricing during peak periods. Moreover, households face a vast assortment of increasing electricity prices and increased awareness for environmental sustainability. The implementation of DSM has been slow due to a number of reasons such as lack of incentives.

The optimization of electricity tariffs offered to consumers by their utility providers is invariably the primary reason given for introducing competitive electricity markets. Dynamic energy pricing research could be grouped into two categories: profit maximization for utility companies or cost minimization for consumers [92].

5.8 Formulating a Mathematical Model of the Consumer's Electricity Bill

Consider the problem of setting tariffs, where the setting of economy 7 electricity tariffs needs to be established to offer financial incentives to domestic consumers who agree to reduce their energy usage when energy demand is high. The form of the electricity tariff structure is one of the first considerations in any optimization problem which involves minimizing electricity costs.

In our case, a mathematical model was developed to calculate the electricity bills for each household type under both the standard tariff (S) and economy 7 tariff (E).
Then, the difference between the bills under tiered rates (standard tariff) and the economy 7 tariff with load shifting was calculated to assist decision making in resetting the economy 7 tariffs.

The key decision is how to minimize the loss of shifting to economy 7 by finding out how much the electricity rates should be paid by the consumers, while still ensuring the consumers save under economy 7 compared to standard tariff.

5.8.1 Consumer's Electricity Bill under Standard Tariff scheme

Then the total monthly bill under standard tariff (S) is similar to Equation (5.2).

$$S = Q_F . x_1 + Q_2 . x_2$$

And the total electricity consumption (Q) will be

$$Q = Q_F + Q_2 \tag{5.4}$$

5.8.2 Consumer's Electricity Bill under Economy 7 Tariff scheme:

(a) Without load shifting

Then the total monthly bill without load shifting under economy 7 is similar to Equation (5.3).

$$E = Q_F . x_3 + Q_4 . x_4 + Q_N . x_5$$

And the total electricity consumption will be

$$Q = Q_F + Q_4 + Q_N \tag{5.5}$$

(b) *With load shifting*

If

$Q_{sh} =$ part of Tier 2 load shifted to night period(kWh),

The new electricity bill under economy 7 with load shifting will be

$$E_{sh} = Q_F . x_3 + (Q_4 - Q_{sh}) . x_4 + (Q_N + Q_{sh}) . x_5 \tag{5.6}$$

If

$Q_4 = KQ_2$ Then $Q_N = (1 - K)Q_2$

And if $Q_{sh} = yQ_4 = KyQ_2$ Then

$$E_{sh} = Q_F . x_3 + (1 - y)kQ_2 . x_4 + (1 - k + ky)Q_2 . x_5 \tag{5.7}$$

Where k is the percentage of exrea usage (Q_2) used as tier 2 usage under Economy 7 tariff, and ky is the percentage of exrea usage (Q_2) shifted to night period.

The difference between the consumer's bill under both economy 7 tariff with load shifting and standard tariff is obtained in Equation (5.8).

$$E_{sh} - S = Q_F.(x_3 - x1) - Q_2 x_2 + (1-y)kQ_2.x_4 + (1-k+ky)Q_2.x_5 \qquad (5.8)$$

Simplifying, we obtain:

$$E_{sh} - S = Q_F.(x_{31}) + Q_2(x_{52} + kx_{45} - kyx_{45}) \qquad (5.9)$$

Where $x_{31} = x_3 - x_1$, $x_{45} = x_4 - x_5$, $x_{52} = x_5 - x_2$

Using the tariff schemes offered by different suppliers shown in Tables 5.2 and 5.3, the range of variables are:

$23.80 - 23.53 \leq x_{31} \leq 23.80 - 14.93$

$0.27 \leq x_{31} \leq 8.8$

$4.63 - 13.9 \leq x_{52} \leq 5.03 - 9.172$

$-9 \leq x_{31} \leq -411.21 - 5.03 \leq x_{45} \leq 13.288 - 4.63$

$6.2 \leq x_{31} \leq 8.6$

$0 \leq ky \leq 0.25$

Where k is calculated for each scenario, and k_y is in the range [0 - 0.25] based on Figure 5.5.

The aim is to maximize the gain of the consumer through minimizing the difference between the consumer's bill under both the economy 7 tariff with load shifting and the standard tariff ($E_{sh} - S$) by shifting to an economy 7 plan.

Also since changes to economy 7 should result in no change in bill when *ky* is zero, so we have:

$$Q_F.(x_{31}) + Q_2(x_{52} + kx_{45}) = 0 \qquad (5.10)$$

The values of Q, Q_F, Q_2, Q_N, Q_4 and K for the eight scenarios are summarized in Table 5.6.

Table 5.6 Values of Q, Q_F, Q_2, Q_N, Q_4 and K (supplier Y)

	Scenarios							
	1	2	3	4	5	6	7	8
Q(kWh)	145	147	383	246	364	251	369	410
Q_F(kWh)	75	75	75	75	75	75	75	75
Q_2(kWh)	70	72	308	171	289	176	294	335
Q_N(KWh)	22	21	65	47	76	40	67	70
Q_4(KWh	48	51	243	124	213	136	227	265
K	0.69	0.71	0.79	0.72	0.73	0.77	0.77	0.79

The two adults and the two adults with children households represent about half of the energy shifted. As such, the utility companies could focus marketing literature, and any incentives on such consumers. To summarize, we have the following problem formulation for the fifth scenario equation (5.11).

$$E_{sh} - S = 75x_{31} - 289x_{25} + 138.72x_{45} \tag{5.11}$$

5.9 Problem Formulation and Optimization Model

Modeling a problem using linear programming (LP) involves writing it in the language of linear programming. The keys to a linear program are the decision variables, objectives, and constraints. The LP must be converted into a problem where all the constraints are equations and all variables are non-negative.

Decision Variables: The decision variables represent (unknown) decisions to be made. For this problem, the decision variables are the difference between the Tiers' rates. We will represent these unknown values by x_{31} , x_{25} and x_{45} respectively.

Objective: The objective is to minimize the loss of shifting to economy 7 by finding out how much the electricity rates should be so that consumers save more under the economy 7 tariff than under the standard tariff.

The objective is to minimize the function represented in equation (5.13).

Constraints: Every linear program also has constraints limiting feasible decisions. Here we have six types of constraints: $x_{31} \leq 8.8$, $x_{25} \leq 9$, $x_{45} \leq 8.6$.

The basic problem is to find a rate design that prompts consumers to take action to make savings, without undermining the supplier's ability to recover its legitimate costs of operation (to ensure the supplier will not lose), $S = E$ that means,

$75x_{31} - 289x_{25} + 210.9x_{45} = 0$

$75x_{31} - 171x_{25} + 123.5x_{45} = 0$,

Finally we add the linear constraints $x_{31} \geq 0$, $x_{25} \geq 0$ and $x_{45} \geq 0$ to enforce the non-negativity constraint.

5.9.1 Final Model

This gives us the complete model of this problem:

$Minimize \qquad 75x_{31} - 289x_{25} + 138.72x_{45}$

Subject to:

$1x_{31} + 0x_{25} + 0x_{45} \leq 8.8$

$0x_{31} + 1x_{25} + 0x_{45} \leq 9$

$0x_{31} + 0x_{25} + 1x_{45} \leq 8.6$

$75x_{31} - 289x_{25} + 210.9x_{45} = 0$

$75x_{31} - 171x_{25} + 123.5x_{45} = 0$

x_{31} , x_{25}, $x_{45} \geq 0$

The resulting minimization problem is formulated as a linear function of parameters; it can be solved by linear programming (LP) methods.

5.10 Solving the Model using LINDO Optimization Software

In this study, the computer package named LINDO (Linear Interactive and Discrete Optimizer) has also been used to get the solution for the decision problems. The name LINDO is an acronym for Linear Interactive Discrete Optimization. This software has an emphasis on operations research. It is a specialized programme which covers the topics such as linear/non-linear programming and combinatorial optimizations [144].

The LP objective function value and the outputs from LINDO Optimization Software are reported in Table 5.7. From the table, it can be seen that the LINDO package found the optimum solution after 3 iterations (pivots) and an optimum solution has been arrived at with $x_{31} = 0.36188$, x_{25}= 6.369, $x_{45} = 8.6$ and minimize $(E_{sh} - S)$ =620.748.

Table 5.7 Optimal solution of the model

LP OPTIMUM FOUND AT STEP 3		
OBJECTIVE FUNCTION VALUE		
1) -620.7480		
VARIABLE	VALUE	REDUCED COST
X31	0.361880	0.000000
X25	6.369831	0.000000
X45	8.600000	0.000000
ROW	SLACK OR SURPLUS	DUAL PRICES
2)	8.438120	0.000000
3)	2.630169	0.000000
4)	0.000000	72.180000
5)	0.000000	-1.000000
6)	0.000000	0.000000
NO. ITERATIONS= 3		

5.11 Electricity Tariff Optimization

For electricity tariffs to be effective, it is essential that the tariff offered is designed in a way as to adequately motivate consumers to change their electricity usage behaviour. In order to propose a new rate design, the dataset which was derived from the optimum solution achieved in the last section and standard tariff rates presented in Table 5.2 is used for the calculation. Based on the optimum solution shown in Table 5.7 and the value of Standard tariff tier 1 rate (x_1), the results of the proposed rates are shown below:

For: x_1 (Standard tariff Tier 1 rate) = 19.91 p/kWh, the other tier rates have been calculated as follows:

x_3 (Economy 7 tariff Tier 1 rate) = 19.91+ 0.36188 = 20.27188 p/kWh

x_5 (Night rate) = 9.84-6.369 =3.47 p/kWh

x_2 (Stand. tariff Tier 2 rate) = 6.369 +3.47=9.84 p/kWh

x_4 (Econ. 7 tariff Tier 2 rate) = 8.6+ 3.47 =12.07 p/kWh

5.12 Consumer's Electricity Bill under a New Tariff Scheme

The calculation performed was intended to determine if households would benefit naturally from the adoption of the new economy 7 tariffs scheme. To answer this question, a comparison between consumer's bills from each household type under the standard tiered rates and new designed economy 7 rates was performed as shown in Figure 5.9. From the figure it can be seen that, with no load shifting, the single adult, single retired, and two retired households would not be expected to benefit naturally from the new rate of economy 7 tariff, while the electricity bills under both tariff schemes for two adults, two adults with children, and three adults with children households, are the same. It is clear that the single adult with children and three adults or more households would be expected to benefit naturally from the new rate of economy 7 tariff.

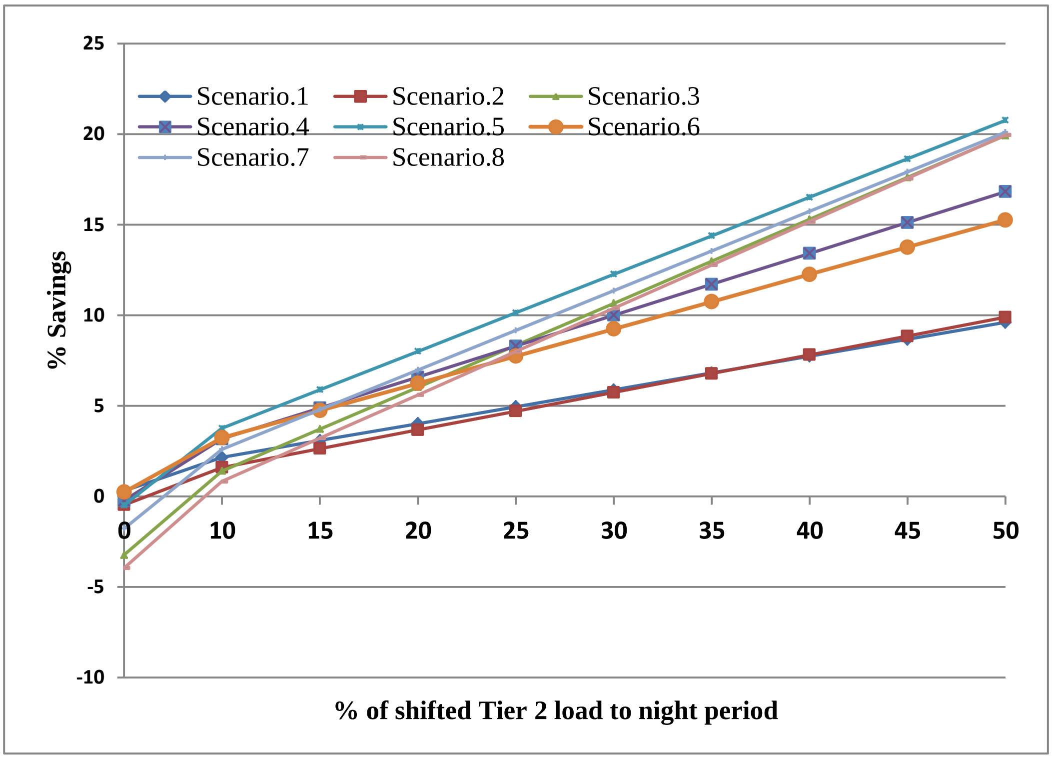

Figure 5.9 Percentage savings in consumer's bill using a new economy 7 tariff compared to standard tariff

If the load is now shifted from Tier 2 to the night time, there could be possible savings. Figures 5.10 shows, for each scenario, the savings compared with the standard tariff (negative indicates loss). The results indicate that, a minimum of 20% load shift is required for single adult and single retired households to benefit from the adoption of the economy 7 tariff. However, a load shift of about 5% is sufficient for scenario 6 (two retired household) to benefit.

The previous calculations were all done by numerically shifting the load. However, in practice, it is the usage of appliances that has to be shifted by behaviour. In this section we examine shifting the usage of appliances such as washing machines, tumble dryers, kettles and irons to a bit earlier in the morning (before 8am). Table 5.8 shows the shifts and gains made with various changes in appliance usage. The table shows that with a significant amount of change in behaviour from the consumer, the total amount of load shift was only around 23%. At this level all consumers get a benefit range from around 2 to about 12 percent.

Table 5.8 Percentage savings in consumer's bills using the economy 7 tariff compared to the standard tariff for different schemes of load shifting

Load shift	i	ii	iii	iv	v
% of Tier 2 load shifted to night	9	17	20	21	23
Scenarios	% Savings				
1	1.8	3.2	4	4.4	4.7
2	1.8	3.1	4	4.8	4.9
3	0.9	4.1	6	7.8	7.9
4	2.9	5	7	7.8	8
5	4	6.2	8	9.5	9.8
6	3	5.1	6	7.8	8
7	2.9	5.2	7	8.8	8.9
8	1	3.1	6	7.9	8

The benefit to the utility company would be dependent on what rates they actually purchase the electricity at. If the cost is significant, then there may be an incentive to invest in trying to change the behaviour of the consumers. However, the focus of any attempt should more focus on the type of households where the benefit would be significant. The two adults household (scenario 4) and the two adults with children household (scenario 5) represent about half the energy shifted. As such, the utility company could more focus on marketing literature, and any incentives on such consumers.

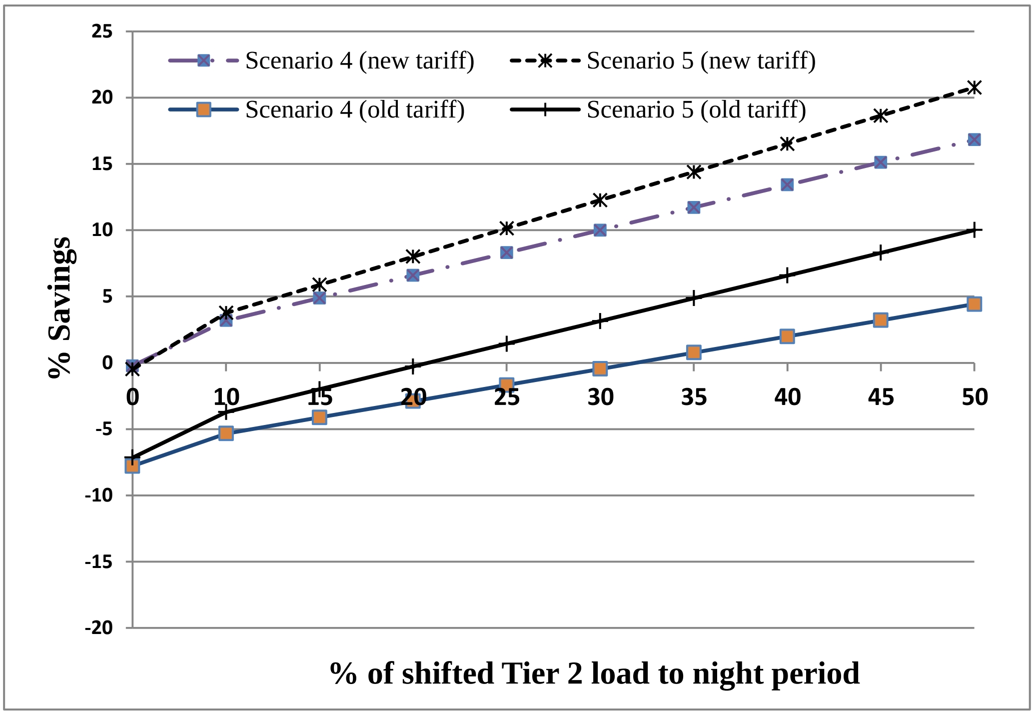

Figure 5.10 Percentage savings in consumer's bills under new proposed tariffs and old tariffs for scenarios 4 &5

If the load is now shifted from Tier 2 to the night time for scenarios 4 and 5, there could be possible savings. Using a standard tariff scheme as baseline, the new proposed tariff and old tariff are compared. Figure 5.10 shows, for scenarios 4 and 5, the savings compared with the standard tariff (negative indicates loss). The graph indicates that the new designed rates for electricity tariffs seem to be effective; in old rates; a minimum of 25% load shift is required. However, the use of the new rates was found quite significant.

The percentage savings in electricity bills for all the scenarios, using scheme (v) of load shifting, is shown in Figure 5.11. It can be seen that, at the old tariff level and with 23% of Tier 2 load shifted to the night time period, only a few consumers get a slight benefit. However, the adoption of a new proposed rate using scheme (v) of load shifting would benefit all consumers.

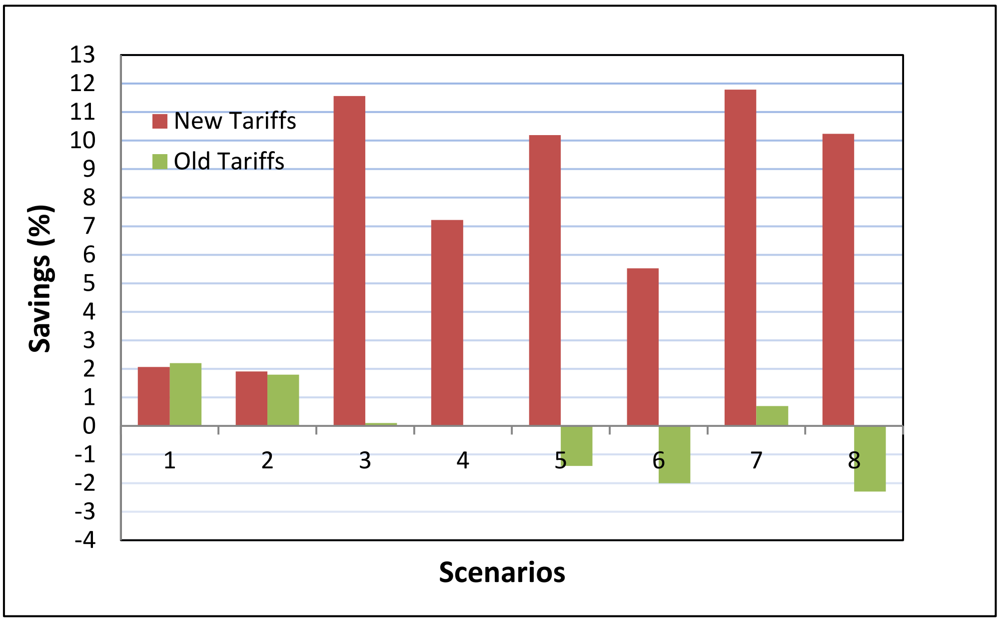

Figure 5.11 Percentage savings in consumer's bills using new proposed tariffs and old tariffs for the eight scenarios

5.13 Discussion

The use of economy 7 tariffs as an incentive to implement demand response in local communities to achieve cost effective peak demand reduction via load shifting was investigated. The tool presented in Chapter 4 enabled the research to simulate changes in customer electricity consumption under economy 7 tariffs, compared to rescheduling the usage time of household appliances. It was found that tariff schemes definitely influence consumer behaviour. The simulation result has shown that economy 7 tariffs hardly have any effect on consumers that have a gas supply as well. The reasons for this are historical and ought to be reconsidered.

Optimization of the current tariffs could possible help shift some of the load at peak hours. However, this was found to be more relevant to particular types of households.

The methodology helped identify such households. As such, the utility company could target marketing literature, and any incentives on such consumers.

From the results it was found that, a simple change of existing standard tariffs to economy 7 tariffs did not provide enough financial incentives for households to invest in DSM technology.

5.14 Conclusion

The conclusions drawn are presented below.

- The use of economy 7 tariffs as an incentive to implement demand response in a local community to achieve cost effective peak demand reduction via load shifting, has been investigated.
- The simulation result has shown that economy 7 tariffs have hardly any effect on consumers that have a gas supply as well.
- A model for optimization of residential electricity tariffs in the presence of load shifting including problem formulation and solution was proposed.
- Current tariffs are not sufficient to change consumer behaviour at peak times as there is little benefit to them in financial terms.
- The analysis helps to determine the suitability of adopting demand response in the domestic sector at community level.
- Mechanisms for local communities may be required to encourage shift in load. This could be via newer energy companies acting as local distributors for a local area.
- The results enable suppliers to focus on the particular types of households to market load shifting techniques to.

Chapter 6

Investigation of Renewable Energy at Local Community Level

6.1 Introduction

The main resources used to generate electricity worldwide are non-renewable fossil fuels such as coal, gas, and oil, as well as non-renewable nuclear materials. Natural gas and coal are the most common fuel for electricity generation, used in 46 percent and 28 percent of the UK's electricity generation.

The need to move towards sustainable energy solutions is highlighted by the increasing greenhouse gas emissions resulting from the use of fossil fuels. Currently, renewable energy sources are considered a possible way to solve world energy and environmental problems. Investment in renewable energy sources would mean that the UK would be able to produce energy cleanly and locally, reducing the reliance on imported fuel supplies.

Renewable energy generated on a local community, rather than national can be considered one of the key solutions to current global challenges. But it is also vital for renewable energy projects to be developed by or with the close involvement of local people, and to ensure a local community experiences benefits within relatively short time periods. Rather than producing a large amount of energy in limited places and using very inefficient long distance transmission cables to deliver it, it is possible to produce smaller amounts of power in many places from the most appropriate

renewable sources. Energy can then be fed back into the distribution network, or potentially consumed locally via localized distribution networks.
Out of all the renewable resources, solar power and wind power are currently the most popular options around the world for producing electricity.

One of the most promising renewable energy technologies is photovoltaic (PV) power. PV systems are a truly elegant means of producing on-site electricity from the sun without noise, pollution or any moving parts. It is estimated that one hour of solar energy received by the earth is equal to the total amount of energy consumed by humans in one year [93]. Over the past years there has been growing interest, across Europe, in the use of photovoltaic (PV) panels for the production of electricity in urban environments. Current UK Government policy appears to focus on large-scale renewable energy production schemes [94], which often attract much public concern and frequently fail to achieve planning permission. By encouraging small-scale schemes, the public may feel more inclined to make a contribution to reducing emissions and could eventually contribute a significant amount of electricity into the energy market.

The chapter aims to use the methodology developed in Chapter 4 to investigate the possibility of using renewable energy (RE) at community level. The evaluation of the cost-effectiveness of the building integrated photovoltaic roofing system when connected to the utility grid has been taken as an example. Using the current utility rates and the energy consumption data, the payback period of the system is evaluated.

6.2 Energy Supply in the UK's Domestic Sector

The UK's residential sector consists of about 26 million households, which account for approximately one-third of all electricity consumption. Energy use in the UK is based mainly on fossil fuels and accounts for over 97% of emissions of carbon dioxide, the main greenhouse gas [95, 96]. The continued use of these fossil fuels has led to an increase in the production of greenhouse gases, especially carbon dioxide (CO_2). Currently the UK emissions of CO_2 contribute about 2% to the global man-made total [97]. Increased emissions of greenhouse gases will contribute to climate change [98]. The effects of global warming require the level of CO_2 emissions be greatly lowered, which includes reducing the UK's consumption of fossil fuels. Beside the negative environmental impact associated with this situation there are significant concerns about energy security, as the UK is an increasing net importer of fossil fuels [99]. Since the UK Government's energy policy aims are to reduce its greenhouse-gas emissions (GHG) by at least 80% by 2050 relative to 1990 emissions, and to keep secure, various supplies of energy [100], significant changes are required in the way that energy is sourced and used.

6.3 The Solar Resource in the UK

Solar irradiance is absorbed and reflected as it passes through the Earth's atmosphere, and partly converted by dispersion into diffuse irradiance. The total irradiance on the horizontal is known as the global irradiance, which is the sum of the direct and diffuse components [101]. Figure 6.1 shows the global horizontal irradiation arriving at a horizontal surface for locations across the UK and Ireland. Locations ranging from (Scotland) to (South-West England) receive approximately 3200 to 3900 MJ/m^2

(880–1100 kWh/m^2) of global irradiation annually on a horizontal surface, assuming no shading. Insolation varies with time of day and season.

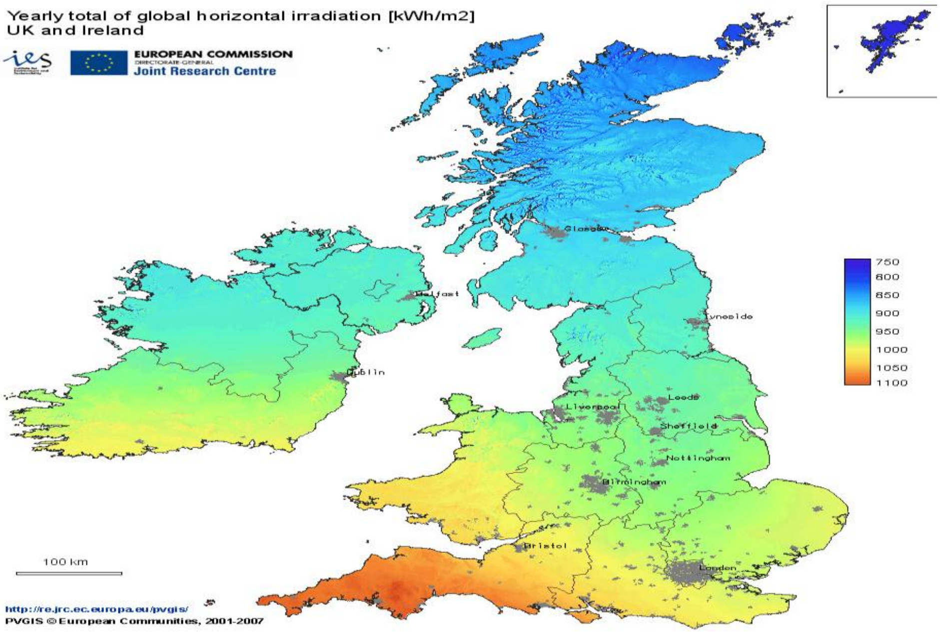

Figure 6.1 Yearly global horizontal irradiation (kWh/m^2) in UK and Ireland

The average daily global irradiation for different locations during different months of the year is shown in Figure 6.2; the data was extracted from the NASA website. From the figure it can be seen that summer days receive a much greater quantity of irradiation than winter days in the UK. During the winter the sun is lower in the sky and hence, ideally, a solar panel would increase its pitch at such times to capture the maximum possible global irradiation.

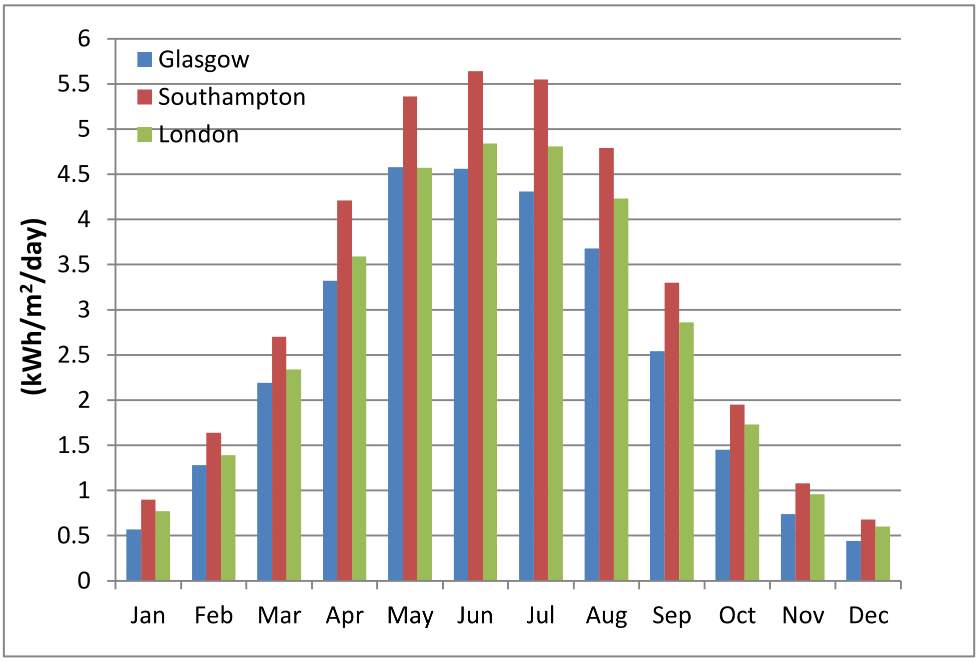

Figure 6.2 Monthly-average solar irradiation during different months of the year

Figure 6.2 also explains the difference between different geographical locations. Southampton receives about 127% of the irradiation received in Glasgow, about 116% that of London and, about 124% that of Bradford.

6.4 Photovoltaic status in the UK

Photovoltaic (PV) energy is the direct conversion of solar radiation into direct current electricity by the interaction of light with the electrons in a semiconductor device or cell. The word photovoltaic actually means "electricity from light". The size of the PV array required by a household depends primarily on the electricity demand, the type of PV cell used, the availability of roof space and budget.

Grid-connected solar PV is the fastest growing energy supply technology in the world, with 50% annual increases in cumulative installed capacity in 2006 and 2007, giving a cumulative total of an estimated 7.7 GW_p.

The PV installed capacity in the UK increased from 18.1 MW in 2007 (over 16 MW grid-connected) [97, 100] to 76.9 MW in 2010. The total energy generated from PV increased from 11 GWh in 2006 to 33 GWh in 2010 [99].There have been significant increases in capacity and generation of PV in recent years due to increased support from government policy incentives. Support in the past has principally been from the Major Photovoltaic Demonstration Programme (2002-2006) and the Low Carbon Buildings Programme (2006 - May 2010), both of which provided support for PV installations by means of capital grants. Support for PV and other microgeneration technologies is now provided through a system of Feed-In Tariffs (FITs) introduced by the UK Government in April 2010, which provide householders and communities generating their own electricity with regular payments through their energy supplier. This may be the main reason for the steady increase of PV use in the UK. Figure 6.3 shows the PV installation capacity in the UK.

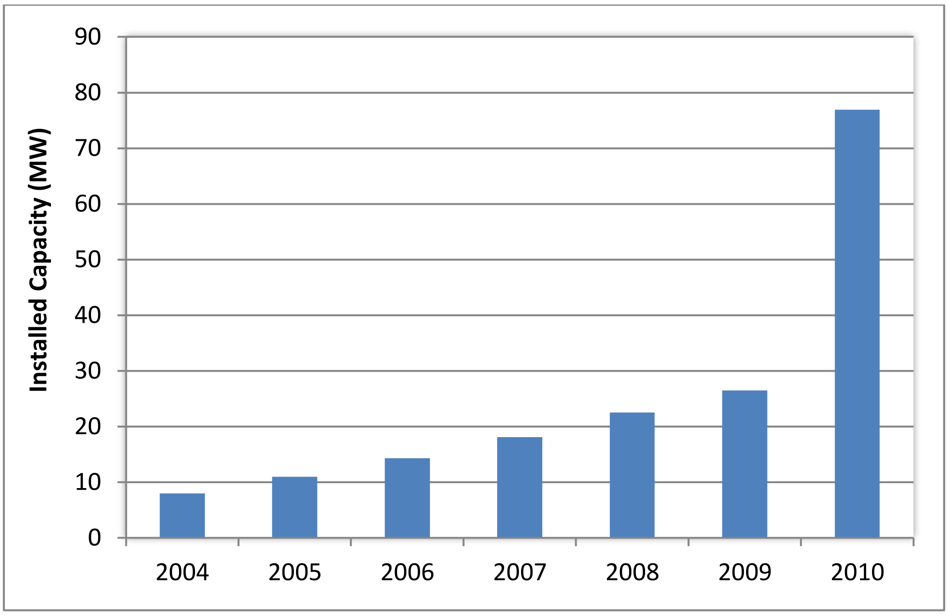

Figure 6.3 PV installation capacity in the UK [102]

6.5 Financial Benefits and Feed-in Tariffs for PV System

Feed-in tariffs (FITs) (also known as the Clean Energy Cash Back) is a collective term which covers everything related to the electricity your PV system generates and how much you get paid for it. Feed-in tariffs (FITs) are not a new concept and have been successfully used in Germany since 1991. They have since been taken up by other countries such as Denmark, Spain and France. The feed-in tariff varies in Europe from between 40 to 50 eurocents, being adjusted depending on the size and location of the system. It was introduced in the UK on 1 April 2010, under powers in the Energy Act 2008. Through the use of FITs, DECC hopes to encourage deployment of additional small scale (less than 5MW) low carbon electricity generation, particularly by organisations, businesses, communities and individuals who have not traditionally engaged in the electricity market. This will allow many people to invest in small scale low carbon electricity, in return for a guaranteed payment for the electricity they generate and export.

Payments consist of a tariff for each unit of electricity generated together with a second tariff for each unit of electricity that is then exported to the grid. Tariffs are linked to the Retail Price Index and support for individual PV schemes has been guaranteed to last for 25 years. Specific tariff levels are dependent on size and type of installation (i.e. retro-fit, new build or standalone).

Installing an embedded generation system that is connected to the grid provides three possible types of financial benefit. Firstly, energy bill savings (Avoided Costs): These are the savings you make on your electricity bill by not having to import electricity from the national grid, and by generating your own electricity ‘on-site’. The amount may depend on how much of the electricity is generated and used on site.

At present the average electricity price for domestic consumers is 13p/kWh [104]. Secondly, if the PV system generated capacity is higher than the base load of the community, it would produce an energy surplus that could be exported to the grid (Export Tariff). The owners get paid an 'export tariff' which is a minimum of 3.1p/kWh. Thirdly, PV system owners are entitled to a generation tariff for each kWh produced whether it is used or sold back to the grid. For small systems installed on existing roofs ('retrofit') this tariff is currently 21.0 p/ kWh. The amount of energy generated is measured by a 'generation meter' installed with the PV system. Feed-In Tariffs (FITs) vary with installation size as shown in Table 6.1.

Table 6.1 FIT Levels for systems

System type	**System size**	**Tariff per kWh generated**
New build	<4kWp	21.0p
Retrofit	<4kWp	21.0p
New build /retrofit	4-10kWp	16.8p
New build /retrofit	10-50kWp	15.2p
New build / retrofit	50kWp-150kWp	12.9p
New build / retrofit	150kWp-250kWp	12.9p
New build / retrofit	>250kWp	8.5p
Standalone	-	8.5p

6.6 Methodology

In order to design a photovoltaic system (PV) and assess its potential contribution to energy consumption, it is necessary to have knowledge of the amount of solar radiation available at the chosen locations. As the energy output depends most significantly on the solar radiation, the input to be used for calculation will be the average hourly solar radiation on a horizontal surface available in Glasgow, Bradford, London and Southampton.

The generated load profile of the virtual community presented in Chapter 4 has been used to study the cost-benefits of a photovoltaic roofing system compared to a non-electricity producing conventional roof. The proposed usable roof area is about 1280m^2. The methodology followed within this study was as follows:

1. Estimate the solar irradiance which is the amount of solar energy that falls on a unit area of a surface per unit of time. It is measured in watt/m^2. As mentioned; solar radiation is identified as one of the most important parameters affecting power production.
2. Estimate the electricity output of the PV system for typical UK installations.
3. Calculate the solar fraction by incorporating estimates of typical household electricity usage, and also estimate the proportion of energy exported rather than used within the household.
4. Estimate the quantity of upstream energy resource and carbon emissions displaced by solar-derived electricity.

6.6.1 Sources of Data

Two types of data were used for this evaluation study to obtain a better understanding of the cost-effectiveness of building an integrated photovoltaic roofing system. These were the average solar radiation data, and the generated load profile previously presented in Chapter 4.

Solar radiation data is essential in order to conduct performance analyses of photovoltaic systems. Hourly radiation data from across the UK from four locations spanning a wide latitude from the lowest at 50º95‟N to the highest at 55 º82‟N was used for the above purpose, as shown in Table 6.2. The average solar radiation for all of the locations selected was obtained from the NASA website [103]. NASA has produced a grid map of the world with information available for any given latitude and longitude.

Table 6.2. Selected locations for the present study

Location	Latitude	Longitude
Southampton	50.95° (N)	1. 4°(W)
London	51.51° (N)	0. 11°(W)
Bradford	53.79° (N)	1. 75°(W)
Glasgow	55.86° (N)	4. 25°(W)

The monthly solar radiation data for the selected locations has been estimated on a half hourly basis, as shown in Figures 6.5 and 6.6.

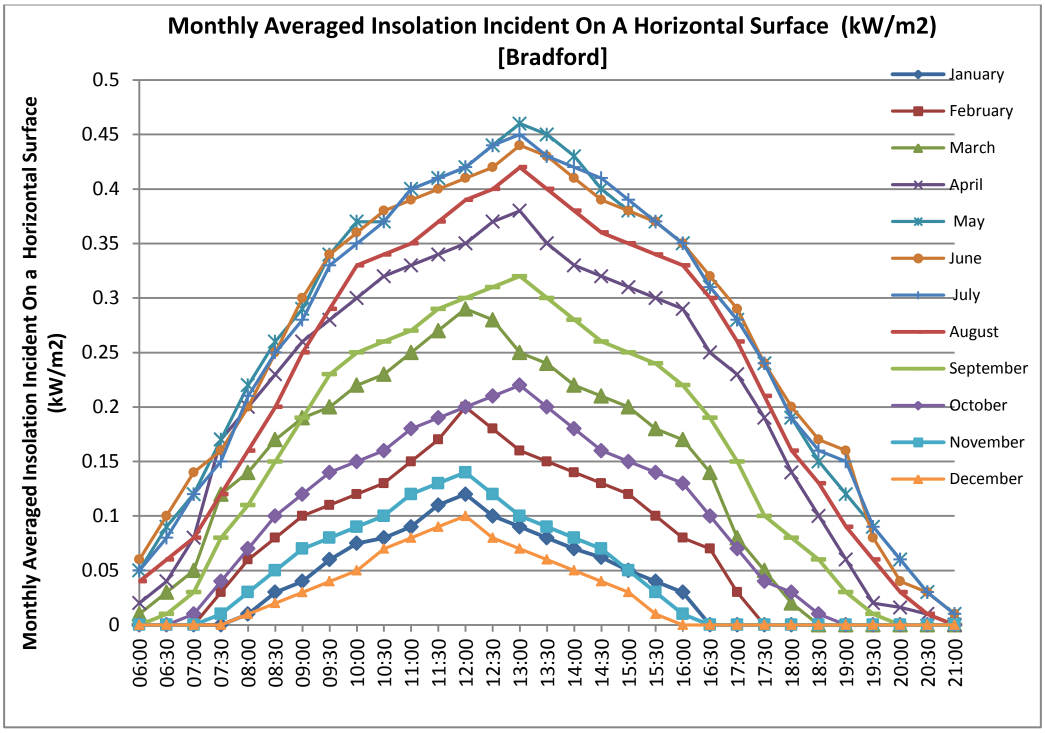

Figure 6.4 Monthly averaged insolation incident on a horizontal surface in Bradford

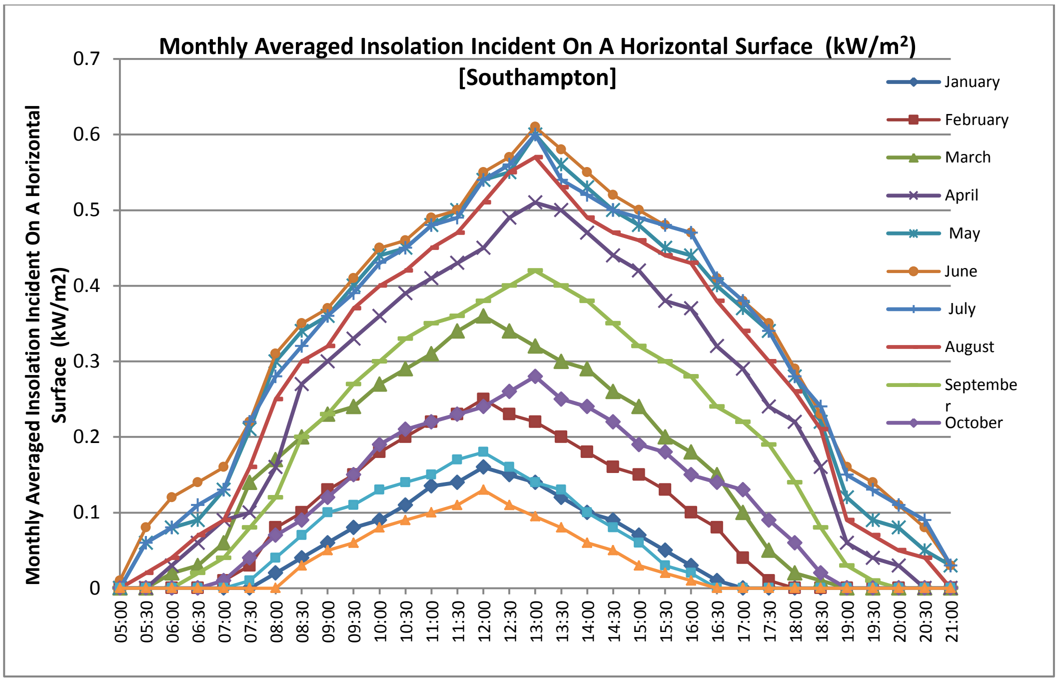

Figure 6.5 Monthly averaged insolation incident on a horizontal surface in Southampton

Table 6.3 shows that the amount of solar radiation is affected by the geographic location and the season. The summer season receives a much greater quantity than winter. The amount of available solar radiation in Glasgow, London and Bradford is lower than that in Southampton. Southampton receives the highest amount of the irradiation while Glasgow receives the lowest amount.

Table 6.3 Average daily insolation levels at different locations

	Glasgow	**Bradford**	**London**	**Southampton**
Month	**Daily Insolation Levels (kWh/m^2)**			
Jan	0.57	0.65	0.77	0.9
Feb	1.28	1.32	1.39	1.64
Mar	2.19	2.22	2.34	2.7
Apr	3.32	3.39	3.59	4.21
May	4.58	4.42	4.57	5.36
Jun	4.56	4.5	4.84	5.64
Jul	4.31	4.48	4.81	5.55
Aug	3.68	3.85	4.23	4.79
Sep	2.54	2.64	2.86	3.3
Oct	1.45	1.57	1.73	1.95
Nov	0.74	0.82	0.96	1.08
Dec	0.44	0.51	0.6	0.68
Yearly(kWh/m^2)	2.47	2.53	2.72	3.15

6.6.2 Electricity demand and PV generation pattern

On a daily basis, the energy in the microgrid powered by several generators can be written as:

$$D \leq \sum_{n} E_n \tag{6.1}$$

Where D is the daily electricity demand and E_n is the energy produced by the generator n.

The total amount of electricity generated by the PV modules is calculated using the following formulation (Equation 6.2).

$$E_n = (R) \times (A) \times (\eta) \times (\eta_i) \tag{6.2}$$

Where, E_n is the PV electricity output; R is the average solar resource (kWh/m^2/day) which includes the direct and diffused solar radiation incident on a horizontal PV panel. A is the module area (m^2), η is the module conversion efficiency (0.13) and η_i is the inverter efficiency (0.9).

As mentioned previously photovoltaic installation outputs are obviously majorly affected by solar variability and the load data. Determining the demand data gives the first idea of the necessary energy required. For PV systems the best option is roof mounted installations. The roofs should be high enough to not be obstructed.

The area of a single PV panel is about 1.6m^2. This can be used to calculate the necessary number of PV panels for the proposed area of roof.

The general assumptions for the calculations are:

• There are 400 households (HH)

• Average PV area: 3.2m^2/HH, with a conversion efficiency of 13%.

• Average single PV panel area: 1.6 m^2.

Area of roofs that are planned to be covered = $400 \times 3.2 = 1280m^2$

If a 1280m^2 area of roof is to be covered by PV, this would require $\frac{1280}{1.6} = 800$ panels .

Given the insolation data previously mentioned and the electricity production per unit area, the total electricity generated by a PV system in half hourly intervals for each month within a given location can be calculated and compared to the electricity loads consumed by the community.

PV systems installed on buildings can supply electricity directly to the electrical appliances within the building or export electricity to the mains electricity grid (Figure 6.6). Export of electricity only occurs when the power generated by the PV system is greater than the loads consumed by the buildings. This situation can often arise when the PV generation is high, such as in the middle of day, and the buildings electricity consumption is low with the occupants at work. PV generated electricity which is supplied directly to the building load decreases the need to import energy from the grid and therefore reduces the electricity bill of the occupants.

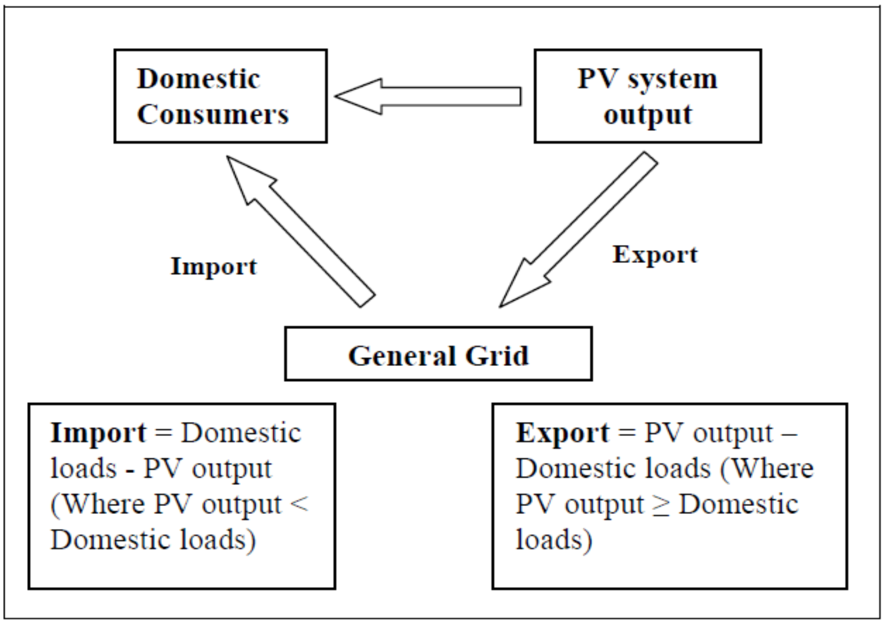

Figure 6.6 Electricity flows in a grid connected building integrated PV system

The PV power is not always generated at the exact time needed by the households. The electricity chart for different months at two different locations is shown in Figure 6.7. The figure shows that all produced energy would be consumed on site because the base load is higher than the maximum power output from the PV panels.

However, the system could prove economically feasible if the roof area covered with the PV panels was increased.

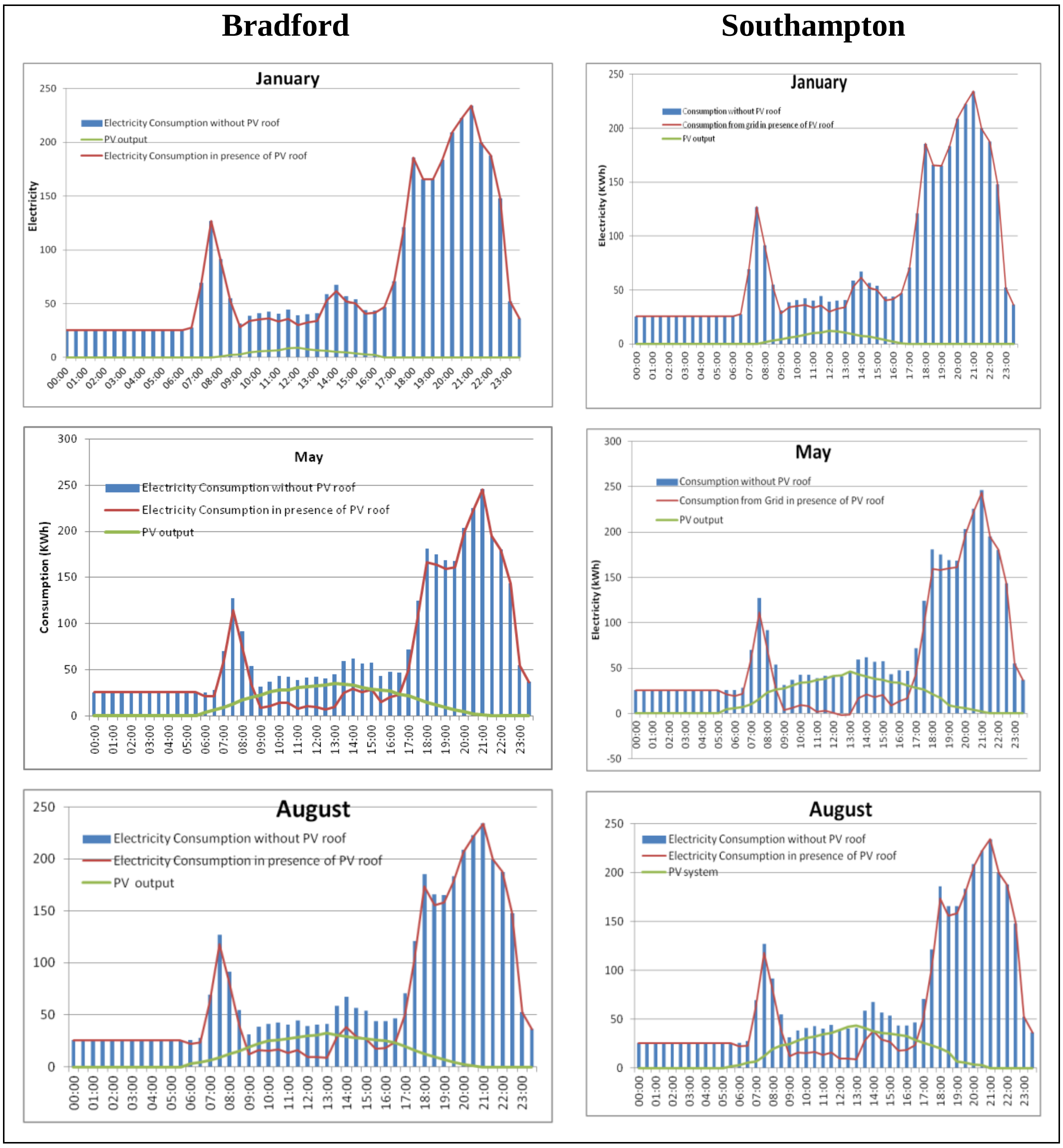

Figure 6.7 Electricity chart for different months

Variations in power output throughout the year are related to solar radiation fluctuations. Seasonally generated power from photovoltaic panels varies significantly. Thus, in May and June PV energy may is about 10 times higher than in December.

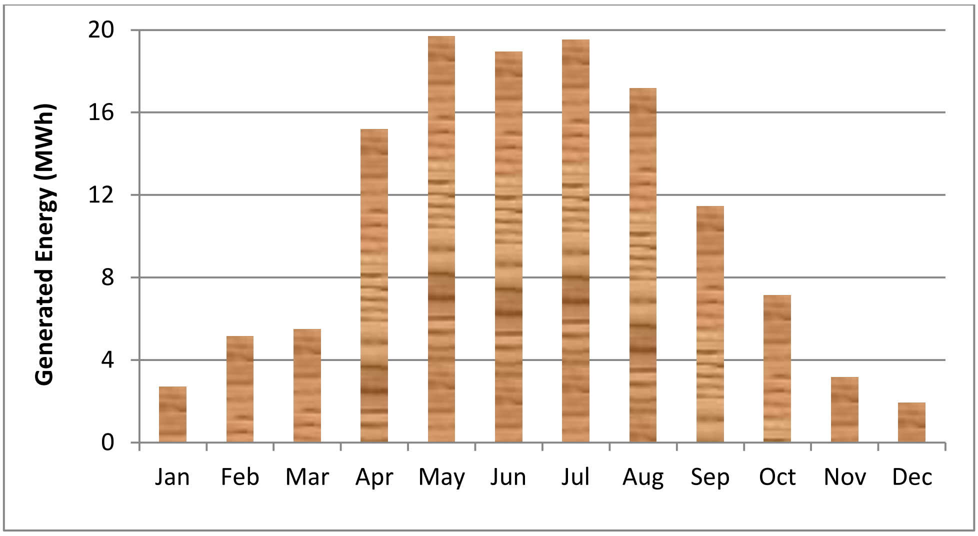

Figure 6.8 Monthly distribution of solar PV generation

The energy gain from photovoltaic panels during the five month period from April to August is the highest, as shown in Figure 6.8. The variance in energy output between months could be explained by different weather conditions, such as cloud cover and the number of sun-shine hours during the year. The total annual energy generated by the photovoltaic system reached about 226.9MWh, and the annual energy demand of the community was about 1,323MWh. As a result 800 PV panels would produce approximately 17% of the energy demand of the whole community for the year.

6.7 Simple Payback Period (PBP) Analysis

The purpose of this study is to assess the impact on the payback period of installing four identical PV systems for a similar community to that presented in Chapter 4, at four different locations.

A simplified form of cost/benefit analysis is a simple payback period technique. In this method, the total cost of the improvement is divided by the first year energy cost savings produced by the improvement. The simple payback period (PBP) can be appropriately defined as the time needed for the cumulative revenue earned to equal the total initial investments, i.e. how long it takes to recover the initial investment made by selling energy. For new construction, it can be used to evaluate conventional construction to energy-efficient design alternatives.

In simple payback analysis, the service life of the energy efficiency measure will be assumed to equal or exceed the simple payback time. Simple payback analysis presents a relatively easy way to examine the overall costs and savings potentials for a variety of project alternatives. While the payback period analysis does not take into consideration the time dependent value of money, nor the total accumulated cost or savings over the life of the system, for systems with equal expected life, the simple payback period can be applied to determine relative performance among alternatives.

$$Simple\ Payback\ Period = \frac{Total\ cost\ of\ the\ system}{Annual\ income\ \&\ savings} \tag{6.3}$$

- ***Without government incentives***

To calculate the PBP with no government incentives, the amount of electricity produced, total annually electricity bill under a standard tariff scheme, and savings during the year, are calculated using the following data assumptions.

Data:

Area of full roof: 1280m^2

Area of panel: 1.6 m^2

Cost of panel: £685 [104]

In this study an assumption of a twenty five year lifetime period for the modules was used. The simple payback period will be calculated under the standard tariff.

Tier 1 tariff (p/kWh)	19.91
Tier 2 tariff (p/kwh)	9.84
Tier 1 Limit (kWh)	225

The typical cost of the PV system of 800 panels, including all components and installation is about £548,000. The results for total electricity generated, total electricity bill and savings are all shown in Table 6.4.

Table 6.4 Total electricity generated, total electricity bill and annual savings without government incentives

Location	**Total electricity generated per year (kWh)**	**Total electricity bill (£)**		**Annual savings (£)**
		without PV	with PV	
Southampton	168618.8	166505	149913	16592
London	145840.5	166505	152172	14333
Bradford	132043.5	166505	153512	12993
Glasgow	128912	166505	153824	12681

Using Equation 6.3 the simple payback period was calculated for similar communities living at different locations, in order to observe at what point the system appears cost-effective compared to the conventional non-electricity producing roofing system. The results are summarized in Table 6.5. From the table, it can be seen that the energy payback time for the PV modules at the four selected locations ranges from 33 to 43.2 years from Southampton to Glasgow.

Table 6.5 Simple payback period at different locations without government incentives

Location	Southampton	London	Bradford	Glasgow
Simple payback time (years)	33	38.2	42	43.2

Since these values have not been discounted, Equation 6.3 will give overly optimistic estimations. However, in the case that external service from PV system adoption offset the discount rate, this would be an accurate representation of the years for a net utility return of zero. Additionally, discount rates may be offset by increasing electricity prices due to increasing shortages of fossil fuel. If this is the case, the PV system would be a good investment for all selected locations with average payback periods less than 40 years. Generating a payback period that does incorporate discount rates gives us the ability to view the strict financial viability of photovoltaic energy as an investment with current prices, electricity costs and PV efficiencies.

- ***With Government incentives***

Using the following data, the yearly amount of electricity produced, total electricity bills and savings are calculated (Table 6.6).

Data:

FIT Generation Tariff: 16.8p/kWh (based on Tariffs valid from 12 Dec 2011).

Export income: 3.1p/kWh (based on Tariffs valid from 12 Dec 2011).

Electricity savings: 13p/kWh (based on Tariffs valid from 12 Dec 2011).

Table 6.6 Total electricity generated, total electricity bill and annual savings with government incentives

Location	**Total electricity generated per year (kWh)**	**Total electricity bill (£)**		**Annual savings (£)**
		without PV	with PV	
Southampton	168618.8	172082	150162	50248.4
London	145840.5	172082	153123	43407
Bradford	132043.5	172082	154916	39349
Glasgow	128912	172082	155324	38404

Using Equation 6.3 the simple payback period under government incentives has been calculated using FIT generation tariff. The results are summarized in Table 6.7.

Table 6.7 Simple payback period at different locations with government incentives

Location	Southampton	London	Bradford	Glasgow
Simple payback time (years)	10.91	12.61	13.92	14.26

For the roof mounted PV system, the payback period at the four locations has been estimated to be from 10.91 years to 14.26 years from Southampton to Glasgow. This is obviously shorter than the lifespan of the PV systems, which is about 25 years. This means that the systems in Southampton and Glasgow will have paid for themselves in less than 11 and 14.26 years respectively. The remaining £703,477 (in Southampton) generated over the subsequent 14 years will be pure profit. The results also show that the PBP varies significantly with the PV installation location. The location of PV systems has an impact on the payback period of the capital costs used to build the system. Capital costs can be recovered over different time scales; therefore the amount of profit that can be made after the break-even point depends on the location of the PV system.

In general, choosing locations with good sun exposure and choosing optimal orientations are the keys to using PV technology economically and sustainably.

The above results indicate that government incentives have a big influence on the payback period, creating conditions that make solar installation an attractive investment. Behaviour change is one of the desired outcomes of this incentives policy on the part of the government.

6.8 Emission Savings of the PV System

The most significant environmental benefit is reducing of greenhouse gas emissions, especially carbon dioxide. Total emissions in the network come from conventional plants. Only CO_2 emissions are considered in this study. Solar power i.e. as a clean source of power has no output emissions. Daily demand level varies at different hours of the day and is being supplied by different generation technologies, resulting in different levels of emissions during the day. Therefore the amount of emission reduced by solar power depends on levels of solar power and demand. The long-term effect of solar power in the network is considered by giving priority dispatch to solar power. This means that for every MWh of solar generation produced at a certain hour during the day, it is assumed that there will be another MWh of power production that will not need to be produced at a conventional plant, at that particular hour or demand level.

For UK grid electricity use, the carbon dioxide emissions factor (2011) is 0.521 kg CO_2/kWh [104]. The annual energy output (AC electricity) of the PV system installed at Southampton was estimated to be 168618.8 kWh. By generating renewable energy, the PV system will reduce carbon emissions by 2196.3 tonnes of CO_2 over 25 years ($168618.8\ kWh \times 0.521\ kg\ CO_2/kWh \times 25$).

In general, by increasing the photovoltaic system penetration it is expected that there will be a reduction in emission levels, as a result of the energy produced by conventional plants being displaced by solar power. This reduction level varies at different locations where the PV system is installed because of the network's impact.

6.9 Discussion

In this chapter, the possibility of using renewable energy (RE) at community level has been investigated. An evaluation of the cost-effectiveness of building an integrated photovoltaic roofing system, connected to the utility grid, has been taken as an example.

The results indicated that government incentives have a large influence on the payback period, creating conditions that make solar installation an attractive investment. The introduction of the feed-in tariff is perhaps the primary reason why the uptake of PV has increased significantly.

Geographical location was seen as an influence on the timing and quantity of solar output. Solar PV benefits can vary widely between UK regions. A significant benefit to PV installation is a lower energy bill, but the magnitude of this benefit depends on the amount of solar energy that can be generated given the available conditions, and the way in which utilities charge for electricity. At peak hours of the day, the electricity produced by a PV panel is very low and almost zero so the effect of the PV system on reducing the peak demand is not significant.

A major benefit of a PV roofing system is that it is located close to the customer. This avoids transmission and distribution costs for utilities. This could reduce losses in the distribution grid and the possibility of mitigated voltage drops to customers.

Although PV currently appears to be an expensive option for producing electricity compared to other energy sources, many countries support this technology because of its promising future potential and additional benefits. As well generating electricity it also reduces greenhouse gas emissions and air pollutants, and potentially presents the opportunity to develop a new industry and create jobs.

The tool developed in this research does not use the dynamic load profile characteristics it only uses the total consumption over the year. As such, using the developed tool does not help in really understanding the effectiveness of introducing PV cells. It is possible to use PV cells as an appliance with a particular behaviour (negative load) and integrate load profile into the tool. This would enable understanding of the interaction between the energy generation and the load within the house.

Another issue is that the PV system of tariffs is based on government incentives and could change. It has in fact recently changed to a lower tariff. The tool can be used only to evaluate renewable energy in conjunction with other interventions. This benefit would be helpful to local planners. The storage required for renewable energies is one example of the need to understand the dynamic interactions.

In the next chapter, a methodology is presented which demonstrates how renewable energy intervention could be analysed using the tool developed for local planners. The tool is really useful only if we can exploit dynamic characteristics.

6.10 Conclusion

The conclusions drawn are presented below:

- Renewable energy integration currently can only be studied using bulk quantities over a long period. This is because of the tariff scheme currently being used. As such, a nationally based decision is more useful than using software tools.
- The dynamic behaviour of the load may be critical to the utilities as the peak load may have serious implications in terms of investment in infrastructure. The tool developed could be used to investigate how renewable energy intervention could be used to help improve the load shape. The tool could include the dynamic model of the renewable energy source. This would help in observing the interaction of renewables with the dynamic behaviour of the households.
- It still would be difficult to price the dynamic interventions of the renewable energy using standard tariffs. This is explored in the next chapter.

Chapter 7

Development of Pricing Criteria at Community Level

7.1 Introduction

In the UK there is no real time retail market, and hence no real time retail electricity pricing. Therefore domestic electricity consumers in the UK pay electricity prices that do not vary from hour to hour, but are rather some kind of average price. The key question is whether we can evaluate energy management and renewable energy intervention in the behaviour of customers in real market terms.

Currently only behaviour changes with respect to total consumption can be evaluated. Interventions cannot be defined for peak load behaviour. The effectiveness of the introduction of renewable energy is also hard to assess. Therefore, it is hard to justify introducing of renewable and demand side management at local community level, apart from when following government approved schemes, subsidies, and other initiatives. The government sets legislation such as carbon targets or subsidies, such as for PV cells. These help the UK Government meet EU 2020 climate and energy targets, and ensure that the cost of renewable energy falls over time. The UK Government's Climate Change Bill in 2007 set a legally binding target of a 60% reduction in national CO_2 emissions by 2050 compared to 1990 levels [11].

In this chapter, a criteria will be developed to help developers and planners of local communities to understand the cost of intervention, in order to evaluate where the load is when the prices are high.

7.2 UK Electricity Market

Electricity is an asset which can be bought, sold or traded, but cannot be easily stored like other goods. It could be stored in batteries or in the form of energy by pumping water into storage. The difficulty in storing electricity forces the generation to match the demand at any time. Otherwise there will be power cuts as seen in many third world countries.

The restructuring of power markets has been ongoing in various countries around the world, including the UK, over the last two decades. Since the early 1990's the UK's electricity industry has changed from a government controlled monopoly to a competitive market in order to deliver a lower cost to the consumers, giving consumers the choice to select their energy supplier. In the process a commodity market for wholesale electricity transactions was established. Here electricity is traded in large volumes, mostly between electricity producers (selling the output of their power stations) and electricity suppliers (buying what their customers need).

There are four components to the electricity industry. These components are generation, transmission, distribution and retailers. The generation sector is the production process of electricity in power stations. Transmission refers to the transportation of electricity through high voltage cables. Distribution is the transportation of electricity at lower voltages and facilities to the final customers. Retailers are the people who make the sales of electricity to the final customers. Electricity markets can also be divided into wholesale, retail and balancing markets.

The wholesale market in the UK is the market for the sale and purchase of electricity between retailers and generators of electricity. The current trading arrangements in the wholesale market allow suppliers to buy the electricity they need to meet their customer’s needs from the generating company of their choice, i.e. this is a competitive market.

The retail market is the market for the sale and purchase of electricity between consumers of electricity (customers) and retailers of electricity (suppliers). The current trading arrangements allow individual consumers of electricity to choose their supplier, i.e. it’s a competitive market.

Retailers and generators try to match their demand and generation, respectively, to their contract levels so that they do not have a surplus or deficit of electricity. This is one of the key objectives of the trading arrangements in encouraging all participants to have contracts covering all of their generation and/or demand.

The generators may generate more or less energy than they have sold through bilateral contracts during the process of electricity production and trading. Retailers may purchase more or less power through bilateral contracts than their customers’ actual consumption, and traders may buy more or less energy than they have sold. Such circumstances are regarded as being in imbalance. This energy imbalance is also bought or sold.

The balancing mechanism market is through the National Grid Company (NGC). The National Grid Company (NGC) will accept offers and bids for electricity close to real time to maintain energy balance, and also to deal with other operational constraints of the transmission system. The balancing mechanism allows electricity companies and traders to submit offers to sell energy (by increasing generation or decreasing consumption) to the system. These participants can also submit bids to buy energy (by decreasing generation or increasing consumption) from the system, at a price of the company's choosing. The National Grid Company will take the lowest priced offers and accept the highest priced bids. The imbalance prices, the system buy price (SBP) and system sell price (SSP), applied to imbalances, are derived largely as the weighted average prices of these accepted balancing mechanism offers and bids.

System Buy Price (SBP) is an imbalance price at which retailers settle the deficit in electricity by buying electricity to meet the demands of their customers from the suppliers. If the retailer's actual demand is lower than it has contracted for, it pays the system sell price (SSP) for the excess**.**

7.3 Fuel prices

Household spending on energy is directly affected by the price of different fuels. Fuels used for electricity generation broadly fall into one of three main categories; fossil fuels such as coal, oil and natural gas, which are generally traded on the international market, biomass fuels and nuclear power.

The proportion of net electricity supplied by fuel input in the UK for 2010 was; 46 percent from natural gas, 28 percent from coal, 16 percent from nuclear power, 1 percent from oil, 6 percent from renewable energy sources (including hydro), and 3 percent from other non-thermal sources [1]. The majority of electricity generated is produced from natural gas, coal, and nuclear energy.

The price volatilities of coal, natural gas, and oil can directly impact on the cost of generating electricity. Figure 7.1 shows the trends between fuel prices for coal, gas, electricity, and oil in the manufacturing industry. There is a positive correlation between electricity prices and fuel prices. Over the past five years from 2005 to 2010 the average industrial electricity prices rose by about 54 percent. Over the same period the average gas prices rose by about 25 percent. Average coal prices were remarkably stable throughout the whole period.

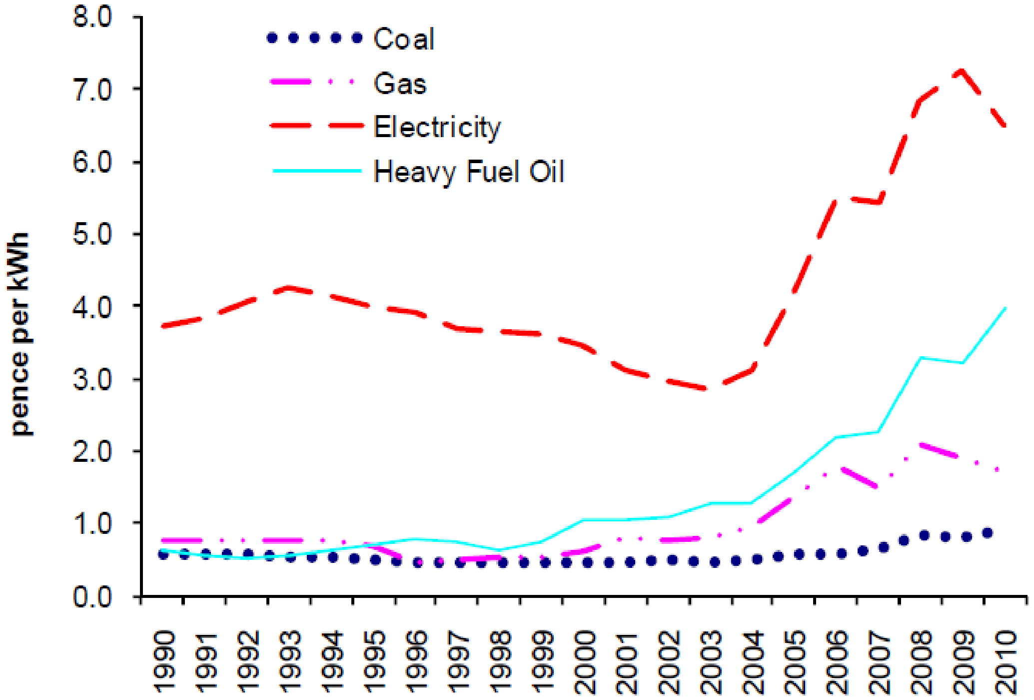

Figure 7.1 Fuel prices for manufacturing industry, cash terms, 1990 to 2010 [105]

The figure also shows that electricity prices went down for the period from 1999 to 2003. This is because of the reform of the electricity market which contributed significantly to improvements in efficiency and productivity, and hence to price reduction. However, after 2003 electricity prices began to rise steeply, maybe due to increasing oil prices, environmental costs and inflation.

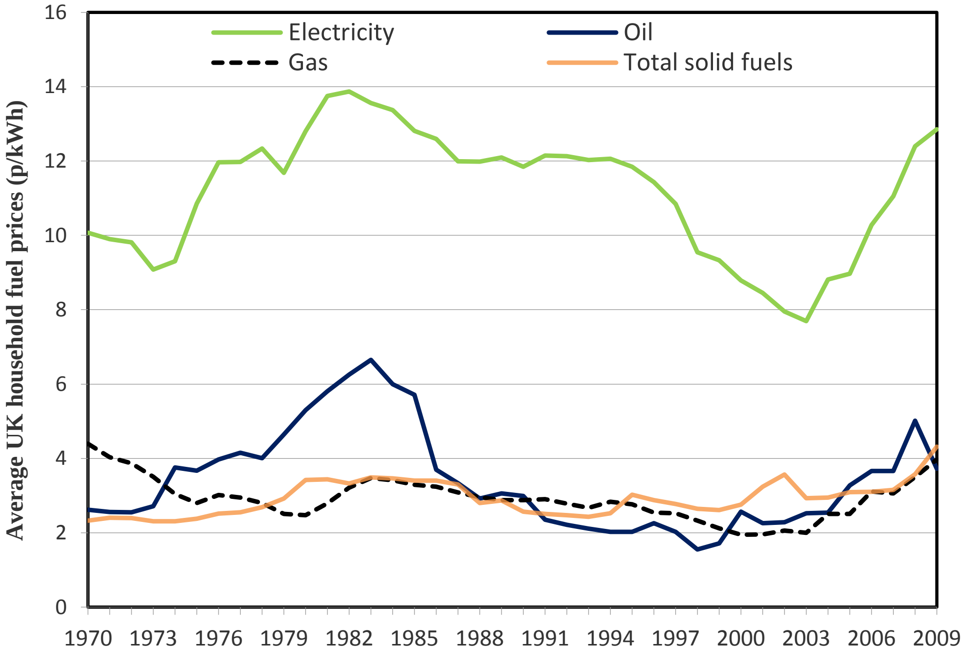

Figure 7.2 Average UK household fuel price [106]

Figure 7.2 shows the average UK household fuel price from 1970 to 2009. The real price of electricity has increased by over a quarter since 1970, and the rise since 2003 has been much steeper: a jump of about 63 percent in only six years. The cost of electricity is higher because of the costs associated with conversion, transmission, distribution and profit margins of private companies. Gas prices went down constantly during the 1980s and 1990s, with the exception of 1995 when VAT was introduced. By late-2000 prices were one-third below 1987 levels. Prices peaked in January 2007 at a level 82% above the late 2000 [107]. Solid fuels include coal or biomass fuels such as wood, charcoal, agricultural residues, and animal dung. The prices of solid fuels have tended to remain stable.

7.4 System Buy Price

System Buy Price (SBP) is the price at which retailers settle the deficit in electricity by buying electricity from suppliers to meet the demands of their customers. It is possible to use the System Buy Price (SBP) as an indicator of electricity real price.

Figure 7.3 shows a sample of the half-hourly electricity System Buy Price for one week, for the time period 09th Jan 2010 to 15th Jan 2010 [108]. The figure shows the half hourly electricity SBP data in pounds per megawatt hour (£/MWh). As can be seen from the figure, there are two key peaks. Monday is an unusual event and has large spikes. This might be due to a sudden failure in the power grid which led to a high increase in prices in a very short period of time.

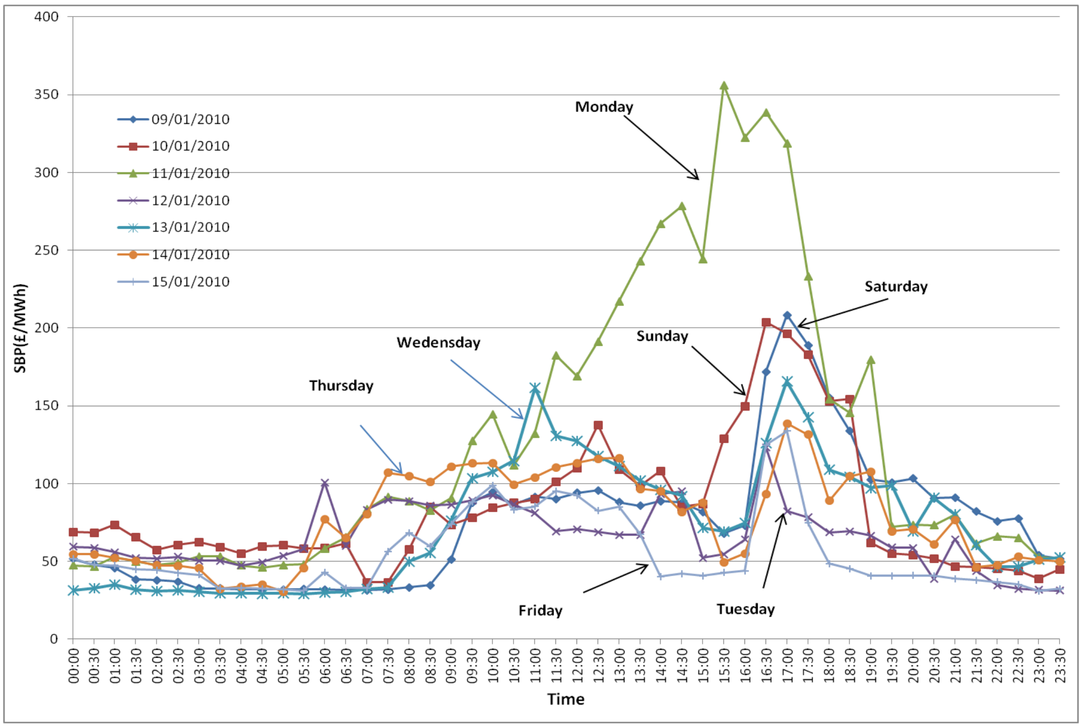

Figure 7.3 System buy price vs. time

The half-hourly national demand data over two days is shown in Figure 7.4. The data was taken from the National Grid website [109].

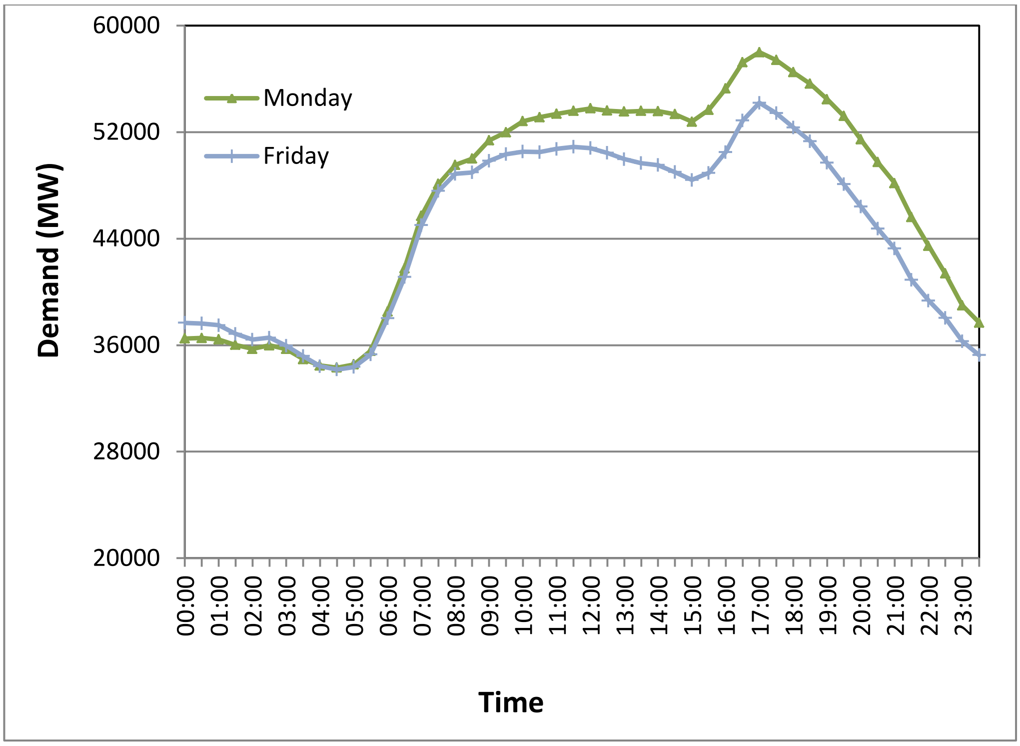

Figure 7.4 System demand vs. time

From Figure 7.4 it can be seen that the demand is more predictable, with less variations between days. The amount of daily demand for the whole data sets (from January, February and March) is approximately the same (ranging from 2244 GW to about 2250 GW). Furthermore, there is only one key peak. We can use the demand as an indicator of price.

Considering Figure 7.3 and Figure 7.4, despite national demand not changing much, we notice peaks at different times of the day. This indicates variations in retailers predicting their own market demand. It also gives us an indication of the price retailers would be prepared to pay in real time rather than in ahead (via contracts).

If, through contractual agreement, the retailer purchases more electricity than required, then the retailer has to sell it back. The price of selling it back therefore indicates whether he is making a profit or a loss. The selling back price therefore would logically be below the contractual price or else market would naturally underbuy on contract. Therefore, the fluctuation in prices indicates the ability of the retailer to accurately forecast his demand in the future and hence the value of his contractual purchases. In other words the retailers' ability to accurately predict will help him to enter contracts in a strong position so that he does not have to buy or sell in the market. In practice, it is not possible to be perfectly accurate as that would require significant management and simulation tools. The market behaviour resolves this in an elegant way. The fact that all companies face the same issues makes the system work to the benefit of all.

The SBP prices were plotted against national demand to give an indication of the way prices rise as demand comes close to the fundamental limits of supply capacity (figure 7.5).

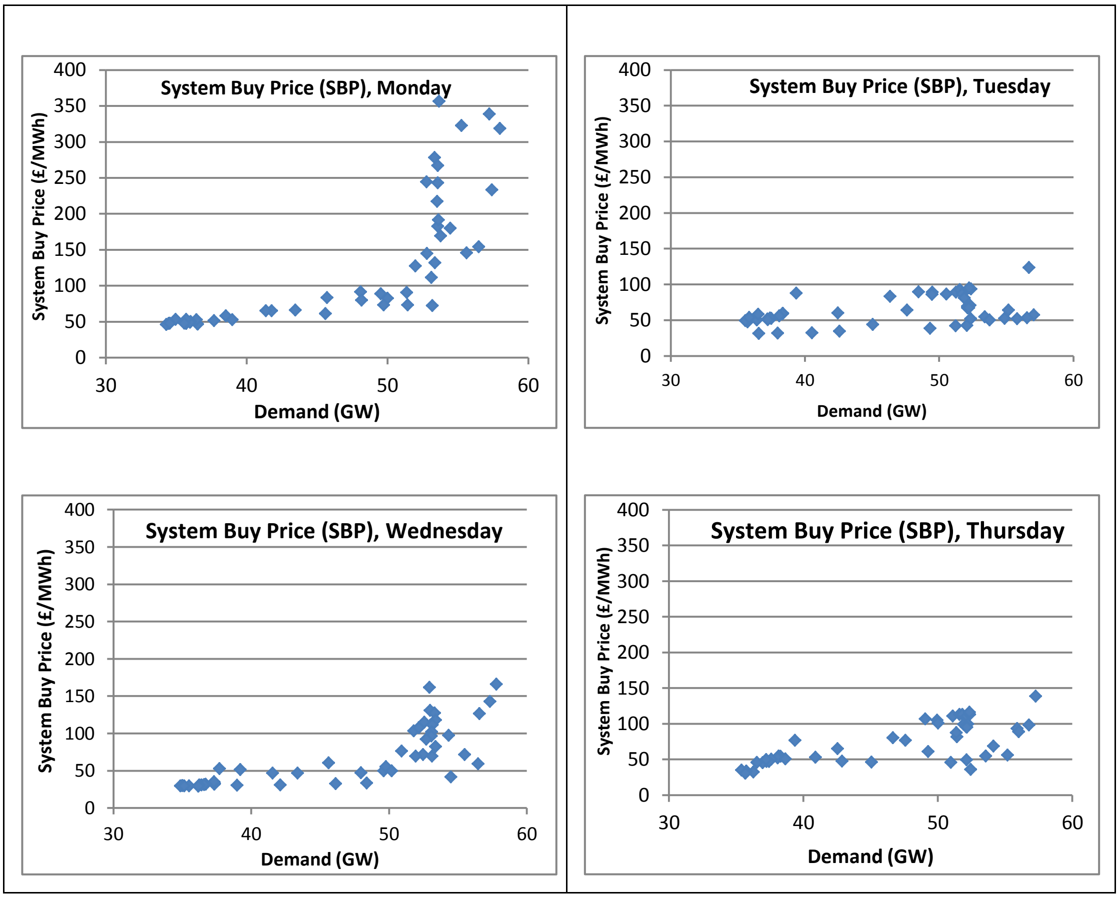

Figure 7.5 System Buy Price vs. demand;

From the figure we can see that big variations occur on Monday and slightly higher price on higher demand points. In order to model this further, a per unit system is developed in the next section.

7.5 Per Unit System

Using per unit values allows essential characteristics of the data sets to be compared on the same diagram. This allows data on different scales to be compared, by bringing them to a common scale. Moreover, different systems can be compared. The per unit system is based on the formula shown in Equation (7.1).

$$\text{per unit} = \frac{\text{Actual Quantity}}{\text{Base Quantity}} \tag{7.1}$$

Base price

The base price is the average half-hourly price. It is calculated as shown in Equation (7.2).

$$Base\ price = \frac{\text{Sum of all half hourly prices}}{\text{Number of half hours}}$$

$$= \frac{\sum_{d=1}^{N}\sum_{i=1}^{48} P_{d,i}}{N \times 48} \tag{7.2}$$

Where $P_{d,i}$ = SBP rate in day d at time i, N= Number of days.

If Equation (7.2) is used in abnormal situation (in sampled case) would result in a big error unless filter out the extremes or use much wider widowed data to reduce the error caused by the abnormal situation.

Base National Demand

The base national demand is the average half hourly demand. It is calculated as shown in Equation (7.3).

$$\text{Base national demand} = \frac{\text{Sum of all half hourly national demand}}{\text{Number of half hours}}$$

$$= \frac{\sum_{d=1}^{N}\sum_{i=1}^{48} D_{d,i}}{N \times 48} \tag{7.3}$$

Where $D_{d,i}$ = national demand in day d at time i,

Base Community Demand

The base community demand is the average half hourly community demand for a day. It is calculated as shown in Equation (7.4).

$$\text{Base community demand} = \frac{\sum_{i=1}^{48} D_i}{48} \tag{7.4}$$

where, D_i = Half hourly community demand at time i,

The base values are calculated for the time period 11th Jan 2010 to 14th Jan 2010 as shown in Table 7.1

Table 7.1 Summary of base values

Base Price (£/MWh)	86
Base National Demand (MW)	46787
Base Community Demand (kWh)	75.3

The results of the calculated per unit values for system buy price are shown in Figure 7.6.

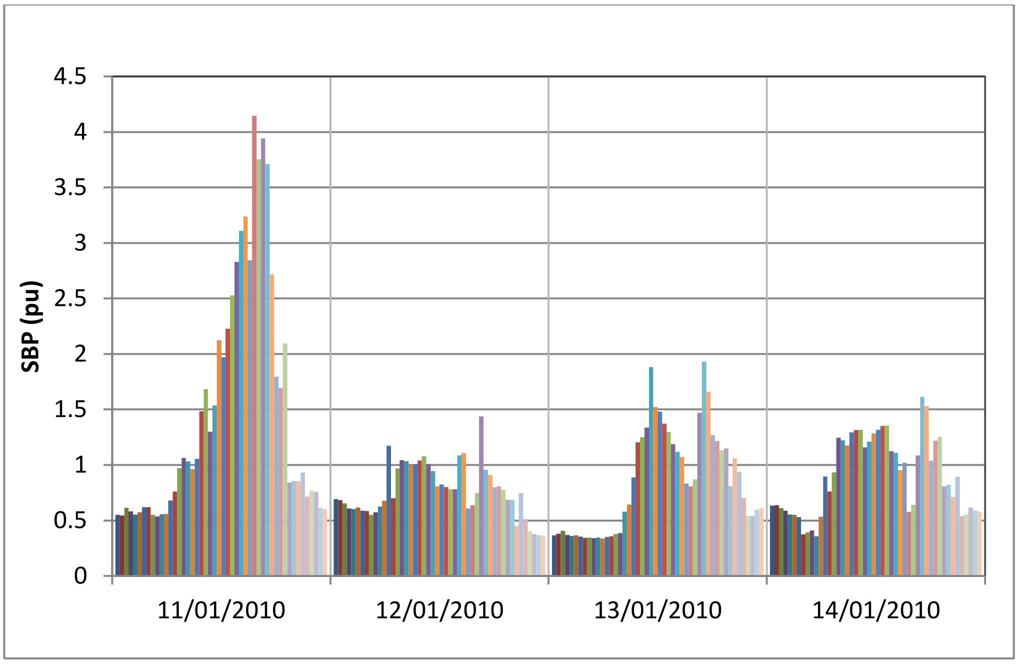

Figure 7.6 System buy price in per unit vs. time

From the figure 7.6, it is clear that Monday (11/01/2010) is an unusual event and the peaks on other days reach near to 1.9 pu. Note that, 1 pu is the average.

7.6 Community Electricity Cost under SBP

The generated load profile for the local community of 400 households presented in giving customers the freedom to choose their energy supplier Chapter 4 has been used to investigate the effect of SBP as an indicator of real time price on the electricity cost for the whole community. We are in need of a measure of dynamic load cost over the day, in order to look at the peak load shaving and a potential for a market.

The community load with SBP prices in per unit for Monday to Friday is shown in Figure 7.7 in a radar chart. As can be seen from the figure, the prices change basically during days and week. Monday is an unusual event and has large spikes.

The electricity cost is the sum of the products of the individual period rates and the energy consumed. Equation (7.5) gives the electricity cost on a time interval.

$$C = \sum_{j=1}^{48} P_j . D_j \tag{7.5}$$

Where: C = total electricity cost to time period T in pu.

P_j = SBP rate at time j in pu.

D_j = Electricity consumed at time j in pu.

If high SBP rates occur during periods of high power demand, consumers can see electricity cost increases above those seen with a fixed rate.

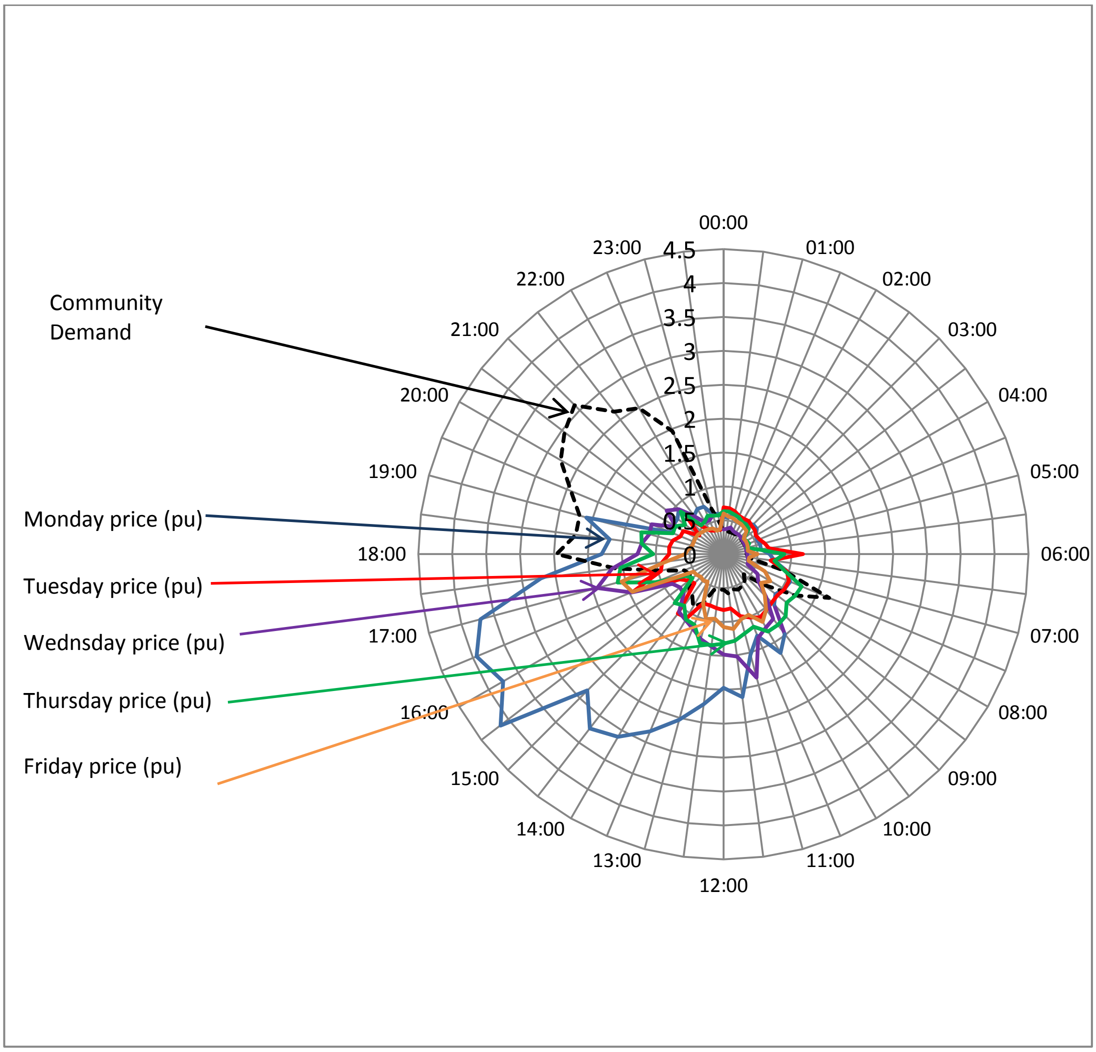

Figure 7.7 SBP rate vs. community demand

The electricity costs of the community have been calculated for each day. The results are shown in Figure 7.8.

Figure 7.8 shows variations in electricity cost. If we use Monday's prices we notice a very high cost around 18:00 and 19:00 of about 4.5 pu, but if we use Tuesday's prices the cost is much lower than on Monday and reaches about 2.3 pu around 21:00 PM. Also, it can be seen that the electricity cost on Thursday is high at 19:00 and 21:00 with a value of about 2.8 pu. Moreover, the peak cost on Friday of about 1.45 pu occurs at 17:00 and 21:00.

The load has a similar cycle but the system buy price (SBP) has a different cycle with different values for each day. As a result, the cost of electricity is different each day (Monday to Friday) reflecting the fluctuation in price**.** From the results we can conclude that it is very difficult to manage as indication of price keeps changing. Therefore, it is not a reliable tool for the planners.

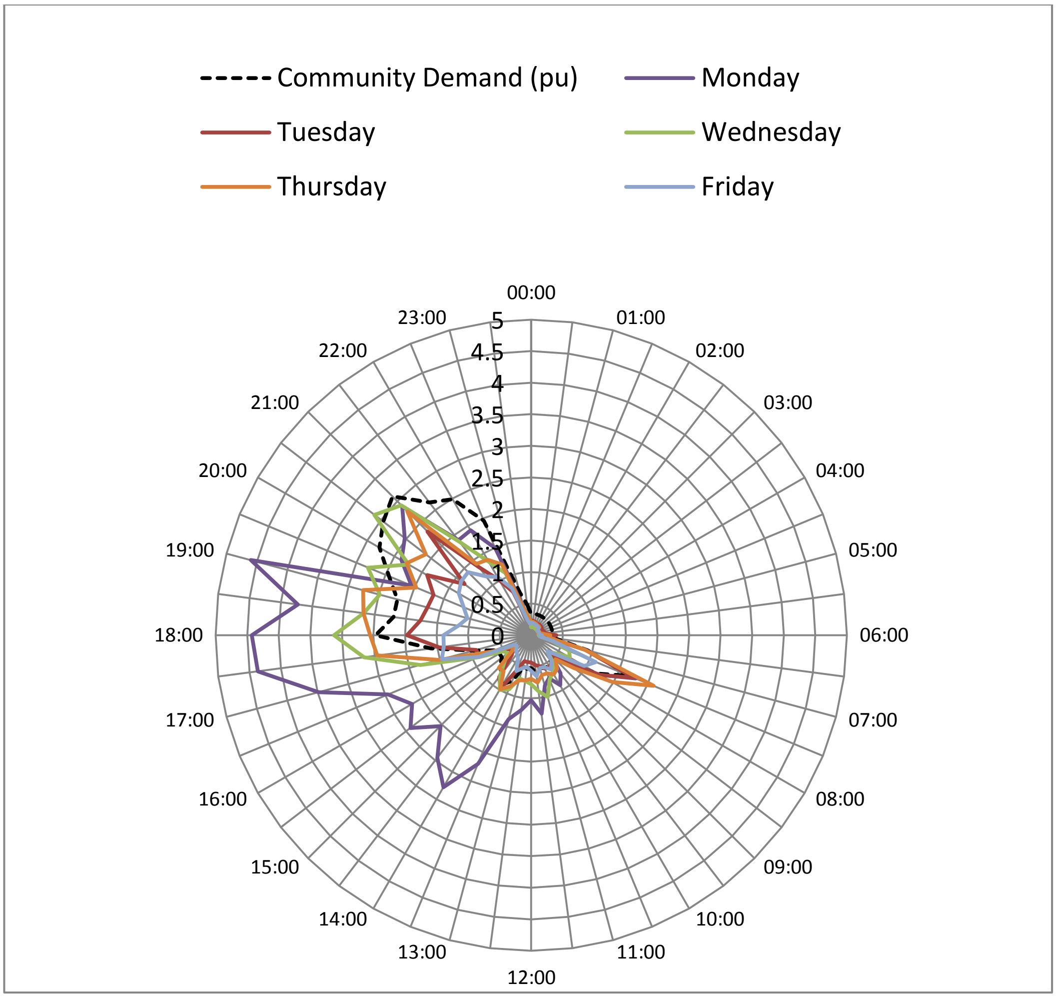

Figure 7.8 Community demand and electricity cost under SBP

Figure 7.9 shows the local demand plotted against national demand. From the figure, it can be seen that the national demand is more stable across the day and has a peak around 16:30 to 18:30. The local residential demand would naturally have peaks at different times of the day. As a result of that, investments to reduce bills under standard tariffs would therefore not have a significant impact on natural peak load (between 16:30 - 18:30). Therefore it is difficult to understand what intervention in behaviour is required using purely load behaviour.

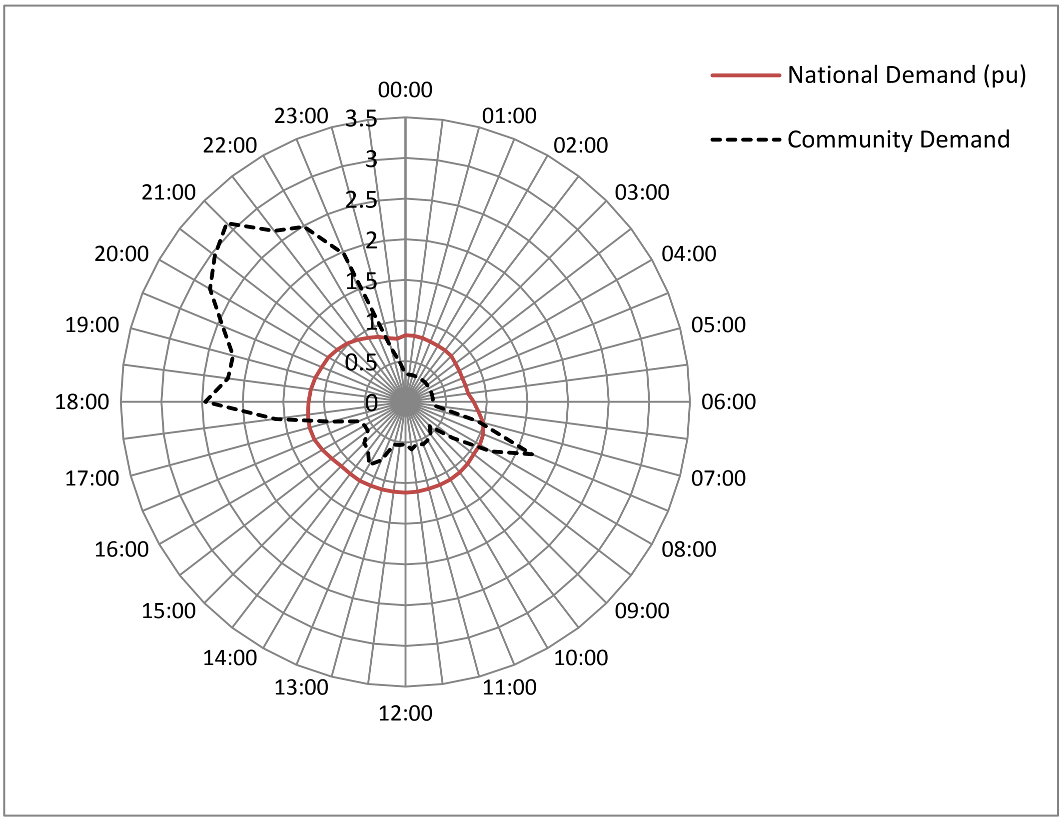

Figure 7.9 Community demand vs. national demand

In order to model further, three possibilities of electricity measure of system price are developed in the next section.

7.7 Price Model

When overlaid the system buy prices data for January, February and March (as shown in Figure 7.10 [106]), the whole data sets are not visually discernible. It can be seen that the supply capacity is in the range of about 55 to 58 GW, and that there is a considerable knee in the curve at around the 52GW, £100/MWh region. Also, there is a spread in price points for demand between 40 and 58 GW.

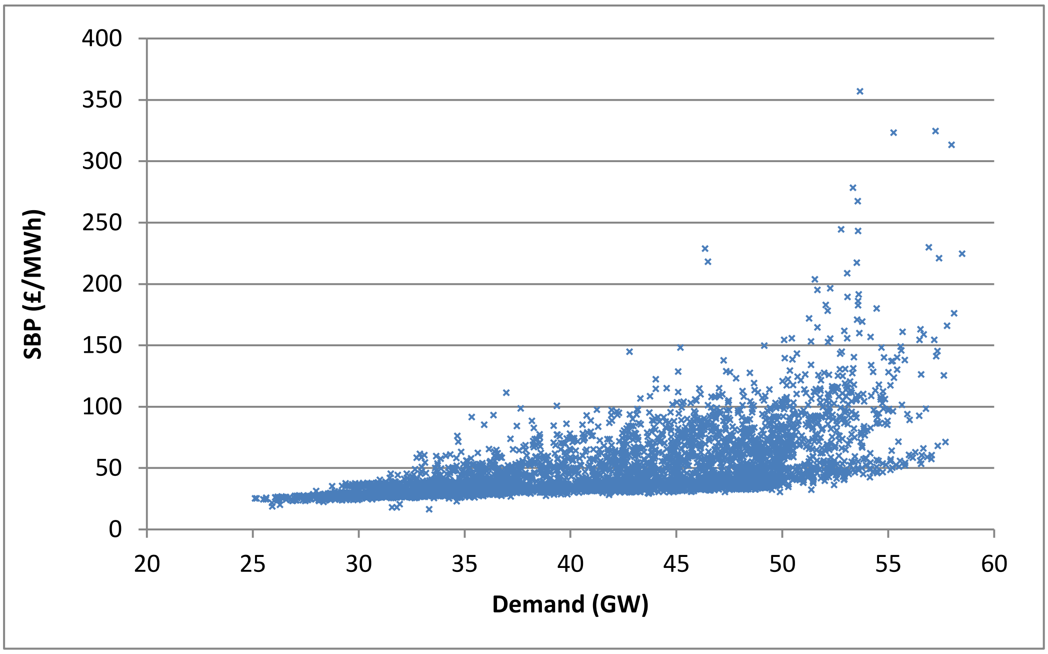

Figure 7.10 System buy price vs. demand (data combined)

Figure 7.10 is not useful in this form, therefore it was decided to use the quartiles as an indicator of range of prices.

There are a number of alternatives which could be used as an indicator of range of prices such as minimum, maximum or quartiles. The quartiles have been used rather than the maximum and minimum values because there is a need for an indicator that considers all the values, and not just the minimum and the maximum. The minimum value to the maximum is the range. The difficulty in assessing by range is that an extreme change in just one value drastically changes the range. So, it is not reasonable to use the maximum or minimum; they could be abnormal. In order to create three quartiles, the sample of 4318 of half-hourly national demand representing three months' data has been arranged in numerical order from smallest to largest. The national demand data is divided into 15 groups with equal intervals of 2250. Each demand group is associated with system buy price data and treated as a separate data. For each group the three quartiles of system buy price (SBP) are calculated. Each quartile is treated as a separate data. The first or bottom quartile represents the lowest price data , the second quartile or median represents the median price, and the third or upper quartile represents the highest price. Each quartile of SBP associated with demand data are treated as a dependent variable and an independent variable respectively, which means we have three dependent variables (bottom, median and upper). Each dependent variable has a single value for each demand data interval. The three fitted price equations for each scenario (quartile) were estimated using regression analysis. The computer statistical package software MINITAB has been used to get the fitted regression equation. The electricity price curves are of the form:

$$price = a + be^{cd} \tag{7.6}$$

Where price is the fitted quartile electricity price in p.u and d is the instantaneous national demand in p.u at that day. The resultant electricity price curves, shown as a function of demand, can be seen in Figure 7.11.

The resultant fitted equations for high, medium and low electricity price curves are shown in Equations 7.7, 7.8 and 7.9 respectively. The determination coefficients for the three quartiles are 0.96, 0.96 and 0.93 respectively.

$$P_{high} = 0.3365 + 1.565 \times 10^{-3} e^{5.502d} \tag{7.7}$$

$$P_{medium} = 0.3282 + 1.4523 \times 10^{-4} e^{7.175d} \tag{7.8}$$

$$P_{low} = 0.108e^{1.47d} \tag{7.9}$$

These equations are only valid for the demand data ranging from about 0.6 pu to 1.3 pu. The constant (a) could probably represent the minimum cost of electricity produced, b is a scaling factor and c represents the rate of change of pricing.

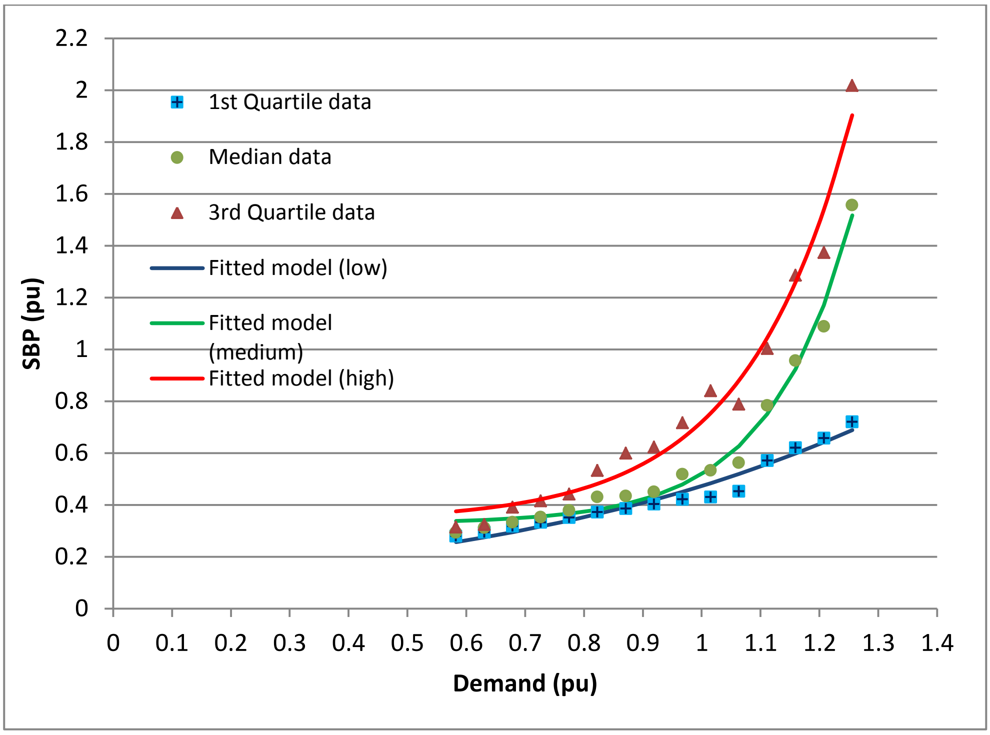

Figure 7.11 Simple model of system buy price vs. demand

The gap between the curves at high demand shows the potential for the market. The curve also shows that at high demand the cost is a significant; up to 2 pu, whereas it can possibly be as good as 0.8 pu. The median curve also indicates that at peak level of demand the price is about 1.5 pu. Structurally, this indicates that for generators it would cost more to invest in additional generation, as this indicates infrastructure costs in future. For planners, this indicates opportunities via understanding of peak load pricing which is based on real data. Moreover, the margin of cost benefit to a local planner can be quantified in financial terms. The base value may change but as the comparison in pu the analysis will still be the same. Updated curves can always be obtained for planners.

The fitted price curves are used in the following section to forecast the half-hourly SBP which were considered as a measure of system price in order to investigate its effect on daily electricity demand.

7.8 Community Electricity Cost under the new Pricing Criteria

In this section we are looking at the community electricity cost using the three price curves. The cost of one day (Tuesday) under the three price curves is shown in Figure 7.12. It can be seen that the community demand is higher at 21:00 but the cost is higher at 18:00. The cost variation at peak is ranging from 1.5 pu to 3.5 pu.

It can be seen that the cost was about 1.5 pu at 18:00 for the low model, 2.4 pu at 18:00 for the medium model, and about 3.5 pu at 18:00 for the high model.

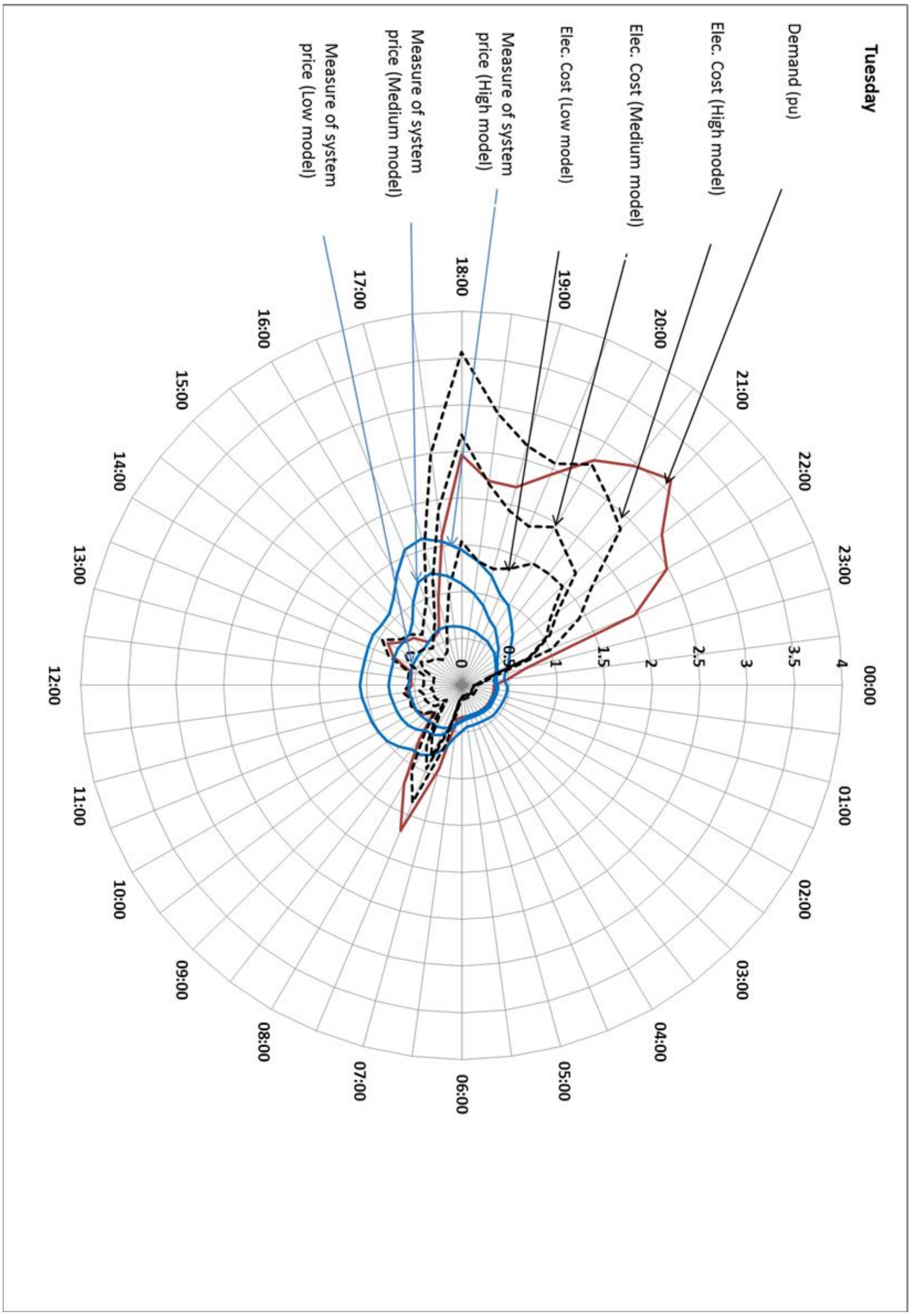

Figure 7.12 Electricity cost under three price model options

From Figure 7.12, it can be seen that the load pattern is not correlated with the price pattern, where maximum consumption periods do not coincide with periods of high price. The electricity cost at 18:00 is about 3.5 pu with demand of about 2.5 pu. This is higher than it is at 21:00 where the cost is about 2.5 pu with demand of 3.1pu.

The issue is that the peak is costing more so we are looking at an idea of costing. The price models are based on national demand where the local community demand has a very different pattern. Attributable to that, the cost curves do not follow the demand pattern. Therefore, the storage batteries could be used as an alternative for peak shaving and load levelling solutions; if we can shift the load a bit we will save a lot more. The planners can now think where they need to make a big effort to evaluate where the load is when the prices are high. An example, to show how we can actually use these curves in evaluating the possibility of using storage elements at community level, is provided in the next section.

7.9 Electricity Storage Elements and Smart Grid

In recent years, there has been greater worldwide attention towards energy storage in order to reduce the perceived risks related with higher penetration of renewable generation (e.g. not available on demand). Energy storage elements have become very important source of fast power transients. Energy storage technologies have great potential to improve the operation of electric power grids and also to support growing in renewable electricity generation Energy storage technology is transform the electrical energy into other forms of energy, and when needed to power in the form of release. Many energy storage options exist and can be classified by their type of storage: mechanical, electrical, electrochemical and thermal. The electric energy storage technology that should be chosen in a certain case depends on the type of application. Pumped Hydro, Flywheels, fuel cells, batteries, thermal energy storage and capacitors are some of the options [139, 140].

Battery technology is the most frequently used method of energy storage. It has been paid significant attention recently because of the attractiveness of plug-in electric vehicles. However, battery technology also has significant potential for grid scale energy storage. Designs being considered for this application include lithium-ion, lead-acid, sodium sulphur, and flow batteries. A battery energy storage system can be used to reduce the peak load and thus reduce the electricity cost by discharging stored energy throughout peak times. Batteries are usually used as an energy storage element. Storage elements are used to balance the variations in primary generation and meet the significant growing electricity demand. Energy could be generated throughout off peak times and this energy could then be stored as reserve power. Storage can play a multipurpose role in the electricity supply network, to run resources efficiently.

Households will plug in their storage elements at night when electricity is cheap, then plug-in during the day when energy cost is expensive and sell that surplus power at a profit. Many storage elements could be used, like batteries, capacitors or electric vehicles (EV).

The need for storage elements and their use in a power system has long been discussed. An overview of the different storage technologies and their use has been presented in [110-115]. Many previous reviews of storage technologies [110] and [111] focused entirely on lead acid battery technology. A study in [110] discussed economic models, control strategies and applications for lead-acid batteries found in US power systems and in [111] the possible future uses are proposed.

Another review carried out in [112] discussed the use of different storage technologies and suggested that in future batteries may not be the most commonly used storage elements for power system application. In [113] several of the commercial achievements in electric energy storage technology were discussed. Some of the emerging applications in power storage like wind farm power stabilization, etc, were also discussed in this paper.

A study [114,115] on energy storage elements will improve the whole reliability, stability and efficiency of the system using the information on power flow in the micro-grid and deal with a unit of the system to flow the power harmoniously between utility grid and micro-grid. In [116] some design and operation aspects of distributed battery micro-storage systems in a deregulated electricity market system were presented. In [117] a financial analysis of different applications of battery energy storage systems (BESS) in power systems was presented. Control power for primary frequency regulation and load peak shaving at industrial end customers were analysed. The results of the value analysis showed that primary control power is the application that most likely will be asked for by utility companies in the next 3-5 years of the study. Other researches [118 –124] showed that a battery energy storage system can provide frequency regulation. In [125] a method to find the optimal battery energy storage capacity and power for a peak load shaving application was presented. The sizing methodology was used to maximize a customer’s benefit by reducing the power demand payment. The minimum payback time was 6 years.

To contribute to the Green House Gas (GHG) emissions in the transportation sector, battery-powered electric vehicles (EVs) have been developed and are now commercially available for daily use [126]. In spite of their short driving range (typically less than 200 km on full charge) [127], the capacity of the on-board batteries seem to be large enough to partly support household electric consumption management [128].The plug-in electric vehicle is an electric vehicle (EV) that includes batteries that can be charged/ recharged by plugging into a source of electric power. It can be integrated into home energy systems, as well as the electric grid. Electric vehicles would use electricity from the grid, preferably during off-peak and nights to charge, then discharge it back into the grid at other times [129-130]. In the process, the vehicles could also provide regulation service to the grid, as needed. This concept is also known as vehicle-to-grid (V2G) [131].

A ‘smart grid’ provides a significant opportunity for residential energy management. It refers to a way of operating the power system using communications, power electronics, and storage technologies to balance production and consumption at all levels [132-135].

A smart grid can be defined as a grid that intelligently brings the consumers and the producers together in order to efficiently deliver sustainable, economic and secure electricity supplies [132]. It allows the power to flow in both directions. A smart grid is needed to integrate increasing amounts of generated or stored power to the grid. The direction of the power flow in the distribution network will change according to the energy reserves and market price [136]. Moreover, smart grids are the way to encourage consumers to participate in managing actively their energy demands. They provide the consumers with the possibility to participate actively in the market, not only as more aware buyers, but also as small producers. Future smart grids with disperse renewable resources will provide a wide range of new features including smart metering, demand side management and integration of storage elements.

Through the exploitation of smart meters, a smart grid allows two-way communication between the utilities and their consumers, where energy management becomes possible for both sides. It will bring consumers the ability to control their energy use, using demand response. Such factors as peak shifting and overall conservation will create a demand response system.

With the deployment of smart meters it is anticipated that load measurements will be available for all homes in Britain by 2019 [137]. Mass roll-out of smart meters is due to start in the second quarter of 2014 and energy firms are expected to shoulder most of this cost. The rollout of smart meters will lead to a major change in how electricity and gas markets operate. To deliver the rollout, energy suppliers will be required to procure and install smart meters for their customers [137].

In the UK, the adoption of smart metering has to incorporate the potential value of additional consumer services, environmental benefits, improving direct consumption feedback to customers, along with more accurate billing. The UK Government has taken the idea of using smart meters as a tool for carbon emissions reductions more seriously than most, and has proceeded with national rollouts of Advanced Metering Infrastructure (AMI). The functionality that is anticipated for electricity and gas smart meters for the UK includes the ability to provide real-time information to an in-home display [138]. It also includes the capacity to communicate with microgeneration measurement devices.

The smart grid will change the way energy is produced, bought, sold and consumed. It could help decrease power consumption during the busiest times on the power grid, improve efficiency and reliability, and reduce the need to build additional infrastructure.

7.10 Storage Battery Payback Period

In this section, we are looking to evaluate the benefits of electricity storage at community level. Community savings using three possible electricity prices will be calculated with a battery storage system. Furthermore, we estimate the battery payback time under the three price curves (Figure 7.12).

In Figure 7.12 the cost curves are shown. The highest cost occurs at 18:00. The community load at 18:00 is about 2.5 pu. The price at peak is 1.45 pu and about 0.45 pu at night for the worst case scenario. For the most likely case, the price at peak is 1.0 pu and about 0.3 pu at night. For the best case, the price at peak is 0.64 pu and about 0.3 pu at night. These prices are summarized in Table 7.2.

Table 7.2 Electricity peak and night prices

Scenario	**Peak price (pu)**	**Night price (pu)**
Worst case	1.45	0.45
Most likely case	1.0	0.3
Best case	0.64	0.3

Assuming a standard car battery is being used to supply some of the load at peak periods. A standard car battery may be around 80 Ah at around 12 volts, which is around 1 kWh of electricity.

The battery bank can be sized based on the real demand of the community at the time of high price. The real demand is calculated by multiplying the load in pu by the community base demand as shown in equation 7.10.

$$\text{Real load} = (load\ (p.u) \times Base\ value\ of\ load) \tag{7.10}$$

$$= 2.5pu \times 75.3kWh = 188.25kWh$$

So we need around two hundred car batteries to store 190 kWh. The physical dimensions are small compared to 400 houses.

Presently, the cost of batteries is about £150 per kilowatt hour of storage. The cost of an inverter to convert battery to mains power is excluded for reasons of simplicity. However, the cost of inverters has fallen significantly over the last few decades. For 2.5 pu, the cost of batteries as a function of energy used will be:

$$\text{Total battery cost} = (\text{load} \times \text{Base value of load}) \times \text{cost per kWh} \tag{7.11}$$

$$= 2.5pu \times 75.3kWh \times £150 / kWh = £28237.5$$

The curves in Figure 7.11 are in pu and represent prices. As they are in pu, if we used the real average electricity tariff price as 1 pu, then we can have a reasonable indication of financial cost/ benefit. Here we use the average electricity tariff for consumers of 13p/kWh [95]. Below is the calculation for cost savings for the three price curves.

For the highest peak price (Worst case for the system), the maximum daily savings of the storage of the system is calculated by subtracting the night charging price from the peak price.

$$\begin{aligned} \text{Cost Savings} &= (Real\ load) \times (Price\ at\ peak - Price\ at\ nig\text{ht}) \\ &= (Real\ load) \times (\text{Difference in real prices}) \\ &= 188.25\ kWh \times (1.45 - 0.45)pu \times £0.13 \\ &= £25/day \end{aligned}$$

Therefore, the annual cost savings from peak shaving is £8932

The technique used to obtain the simple payback period was simply divide the total battery cost by the annual savings produced.

$$\text{Simple Payback Period} = \frac{\text{Total cost of the system}}{\text{Annual savings}} \qquad (7.12)$$

$$= \frac{28238}{8932}$$

$$= 3 \text{ years}$$

Similar calculations provide the cost savings and simple payback period for the most likely price and the lowest peak price. The results are summarised in Table 7.3.

Table 7.3 Annual electricity cost savings & PBP

Scenario	Annual savings	Simple payback period (year)
Worst case	8932	3.16
Most likely case	6253	4.5
Best case	3037	9.3

The storage battery payback times for worst, most likely and best price scenarios, are 3.16, 4.5 and 9.3 years respectively. Therefore, if a true market existed, the planner would be able to predict that the investment would be paid off after three to nine years.

This has been worked out based on the price of electricity at a standard tariff of 13p/kWh. The price could increase over the years as would be expected with increasing fuel price. Therefore, if the battery's life time was longer, then there is a real potential for initiatives in community level battery storage. Furthermore, the cost of batteries should decrease as the technology improves. A standard car battery ought to be used to supply some of the load at peak periods.

7.11 Discussion

In the UK there is no real-time retail market, and hence no real-time retail electricity pricing. Therefore, consumers do not pay based on the real-time price but rather some kind of average price, and hence have no sufficient incentives to reduce load at times of high prices or to shift their demand to other periods.

A criteria has been developed to help developers and planners of local communities to understand the cost of intervention in order to evaluate where the load is when the prices are high. The SBP was suggested to be used as an indicator of electricity real time price.

To better capture the price fluctuations that can occur in real markets, this work took into consideration the diversification in prices the market might have by developing three price curves in Figure 7.11 using the quartiles of SBP versus national demand. Each quartile presents a possible pricing case. The quartiles have been used rather than the maximum and minimum values because there is a need for an indicator that considers all the values, and not just the minimum and the maximum. The minimum value to the maximum is the range. The difficulty in assessing by range is that an extreme change in just one value drastically changes the range. So, it is not reasonable to use the maximum or minimum; they could be abnormal. The three curves are estimated based on the daily national demand data, because the national demand data is predictable and has low variations. These curves are used as an indicator of electricity real time price and demand, and are presented in pu. These curves can help planners to look at the cost of peak shaving, which is essential for developing a financial case for investment in this market.

Presenting the data in per unit value allows underlying characteristics of the data sets on different scales to be compared by bringing them to a common scale and makes the analysis easier.

The radar chart is proposed as the standard chart to compare the per unit values of demand, price and cost for the local community over the full day, at the nationally accepted half-hourly interval. The chart shows the data around the clock, which is often a good way of comparing several sets of performance indicators. The 24 hours of the day are in a continuous cycle. The day does not end at any arbitrary time. Visualizing data in hourly trends gives people something they can relate to in the context of their daily schedules and enables them to see the consequence of this behaviour. Although the line chart makes graphs easier to read it does not give a good indication of time and behaviour. Therefore it is not easy to conclude where problems are. Moreover, the base value is not as important as the peak value. The radar chart by definition will emphasise the peak and not the common dominator. This is critical when looking at peak prices and infrastructure costs. The radar chart provides a useful set of information and picture of performance to help consumers reduce their electricity costs in order to manage their consumption by taking advantage of lower priced hours and conserving electricity during hours when prices are higher.

The developed three curves have been used as a tool to evaluate the possibility of using storage batteries at community level as an example. PV cells or other embedded could also be studied in a similar way.

The battery simple payback time has been estimated. We used the average electricity price as 1 pu. This can provide a reasonable indication of financial cost/benefit. While the payback period analysis does not take into consideration the time dependent value of money, nor the total accumulated cost or savings over the life of the system, the simple payback period can be applied to determine relative performance among alternatives. Economic calculations can be performed using the life cycle cost (LCC) where consideration of costs over the entire lifetime of the PV system (inflation, tax, and depreciation) can be made.

A single consumer using standard tariffs may not see any benefit in changing his behaviour, as he does not gain by shifting load. If real time pricing was introduced, again, how could one expect the individual consumer to participate actively? It would be like expecting everyone to buy and sell on the stock market every day. This gain is unrealistic. However, it is possible for local planners to exploit benefits and gain profit. Hence, the tool can enable this business to exist; trade between the distributor and the local planner.

7.12 Conclusion

The conclusions drawn are presented below.

- Presenting the data in per unit value allows underlying characteristics of the data sets to be compared.
- The radar (spider) chart has been proposed as a standard chart to compare the per unit values of demand, price and cost for the local community for load shaving aspect.
- As no real time retail price exists in the UK, the System Buy Price (SBP) has been used as a measure of the real price based on per unit values. In order to better capture the price fluctuations that can occur in real markets, the three

curves of Figure 7.11 have been developed using the quartiles of SBP versus demand.

- The tool developed in Chapter 4 can now be used alongside SBP to help planners to look at an idea of the cost of peak shaving which is essential for developing a financial case for investment in this market.

- As an example of using the tool and system buy pricing, the possibility of using battery storage at community level has been evaluated and battery simple payback has been estimated. The methodology can be applied to other interventions for load shaving.

- It has been shown that battery storage at community level is feasible, provided a real time market or “near real time” market is established.

Chapter 8

Conclusions and recommendations for future work

This chapter provides a summary and conclusions of the work, and some suggestions for future research based upon the findings of the research.

8.1 Summary

This thesis presented a methodology to predict local consumption patterns for residential consumers at community level. The load forecast tool was used to study the interventions of using the economy 7 tariff to shift load by shifting behaviour. However, the change in behaviour is quite significant. The introduction of PV cells at a community level was only studied using the tool to predict load, and standard PV cell output characteristics. However, the tool was not found to be useful because of the lack of real time pricing mechanisms or criteria. The issue of pricing was investigated. It has been proposed that the national system buy price against the demand is used as the criteria. An example of using storage batteries was used to demonstrate the usage of the tool and the criteria developed to understand benefit.

A block diagram of the methodology being developed for the local planners is shown in Figure 8.1.

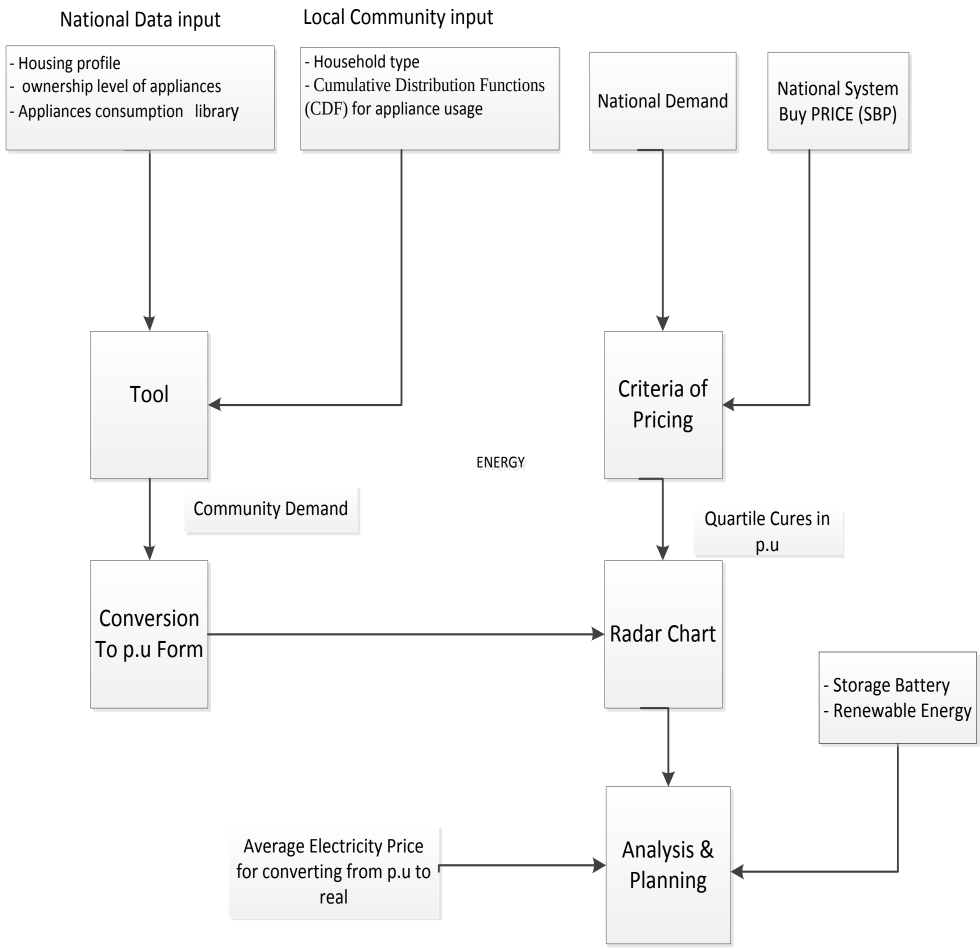

Figure 8.1 Block diagram of the developed methodology

From the diagram, it is clear that the accuracy of the local demand profiles depends on the level of input information. It is possible to improve the database of the tool by obtaining better national representative cumulative distribution functions (CDF) across the country for different groupings and regions, which could be used by local planners. Cumulative distribution functions (CDF) are a good representation of behaviour change.

The criteria for the pricing of cost intervention depend on data that is nationally driven. The actual equivalence of 1 pu is arguable as it differs from supplier to supplier. It is reasonable as an average of standard tariffs would cover the whole country.

Real time retail market issues however affect the analysis on load shaving. Without some forms of real time retail market implementation it is difficult to study storage usage, and the impact of electric vehicles. Smart metering is a technological innovation that may help, but without real time retail pricing, it is perhaps unnecessary. New solutions require not only technical innovation but also behavioural ingenuity by customers and researchers in guiding future electricity use and infrastructure development.

8.2 Conclusions

This thesis makes specific contributions to the field of load modelling and planning at community level where energy demand patterns at this level may significantly differ from the national picture. The contributions from this thesis are summarized below:

In this thesis, the cumulative distribution function (CDF) has been used to present a new methodology which enables the prediction of realistic half-hourly electricity load profiles at residential community level (Chapter 4). It was primarily based on a combination of statistical data, and a questionnaire survey. The cumulative distribution function (CDF) enables the generation of the random nature of consumption. It also indicates a way of understanding behaviour change.

Traditionally, load modelling is done nationally. In this thesis it was proposed to use modelling to examine the energy use on a local level. Modelling at a small residential community level based on a behavioural understanding of the local community can lead to a better understanding of possible interventions. The results show which category of household contributes most to the peak. It is possible therefore to focus energy conservation on those households first rather than the whole community, which may be too costly. This feature of the methodology might be useful to consultants. The methodology therefore can help local planners decide on measures such as embedding renewable energy and demand management.

The methodology developed in this study has been used to investigate the incentives currently available to consumers to see if it would be possible to shift some of the load from peak hours. The adoption of the economy 7 tariff has been investigated, the result has shown that this tariff has hardly any effect on consumers that have a gas supply as well. However, this was found to be more relevant to particular types of households. The methodology helps to identify such households. As such, the utility could focus marketing literature, and any incentives on such consumers.

In this thesis, the possibility of using renewable energy (RE) at community level is investigated. The results showed that without government incentives the use of photovoltaic would not be suitable at the current price.

As it is difficult to obtain the true real time price at consumer level because of the wholesale price, it was proposed to use the system price (SBP) versus national demand as an indicator of the market value.

In order to better capture the price fluctuations that can occur in real markets, the three curves of Figure 7.11 have been developed using the quartiles of SBP versus demand in order to be used as an indicator of range of prices. The proposed curves would contribute to improving knowledge by giving an indication of the real time market price.

In this thesis, the SBP values were normalized and expressed in per unit values, thus allowing essential characteristics of the data sets to be compared: this allows data on different scales to be compared by bringing them to a common scale, and makes the analysis easier.

In this thesis, the radar chart has been proposed as standard chart to look at and compare the local community load and prices. It provides an overall view, with realistic and useful information, and provides a picture of performance which can help local planners to understand and evaluate the system cost at community level.

The possibility of using storage elements at residential community level has been evaluated. The battery simple payback has been estimated. The methodology can be applied to other interventions for load shaving. It has been shown that battery storage at community level is feasible provided a real time market or “near real time” market is established.

As has been shown in this thesis, there is no real time retail market in electricity at local level. It is suggested that a real time independent energy market is introduced to enable transactions at this level.

8.3 Recommendations for Future Work

In this thesis, there are still some improvements which need to be made, and recommendations for future research.

- The method of predicting electricity load profiles at residential community level could be applied for different communities. The limiting factor of applying this method is the availability of the input data, such as occupancy usage patterns. This could be improved by generating national representative cumulative distribution functions (CDF) across the country for different groupings and regions, which could be used by local planners.

- The hot water and heating system load profiles have not been included in this study; it would be possible for these profiles to be included in future work.
- The tool does not consider the variation in load from weekdays to weekend to avoid complexity and this should be considered in future work.
- In this thesis, we have looked at the use of renewable energy at community level; the results showed that the effects of stochastic characteristics of renewable energy generation make the use of photovoltaic is not suitable at the current price without government incentives. This limitation could be addressed by supporting renewable energy generation with an energy storage element which enables people to store energy during off peak periods and use it at peak times.
- A real time independent electricity market at local level has been proposed in this thesis. Developments in the electricity market, storage elements, and smart grids, and the drive for lower carbon generation technologies, where generating and distributing energy is owned and led by communities, will all impact on such a market. The introduction of such an independent retail market at local level to enable electricity transactions between communities with embedded generation capabilities requires further research.
- In this thesis we have looked to model community demand using a bottom up approach. It is theoretically possible that by looking at a power signal of the real load and disaggregating it into its components, it is feasible to extract a reasonable understanding of community behavior. This can be done by using pattern recognition methods and thereby segregating the components.

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Appendix A

The Questionnaire

University of Bradford

School of Engineering

Survey on Household Energy Use

Please feel free to answer the following questions…

I am a research student from the University of Bradford, currently undergoing research on developing a tool for modeling and simulating electricity consumption. The questions that are used in this questionnaire are exclusively for the use of my research and to provide data on electric appliances usage.

The questionnaire is to be completed anonymously, no address, and you will not be treated as an individual participant.

The survey is to be completed by the head of the household and will take a few minutes of your time.

Your help would be greatly appreciated, thank you very much for your time and cooperation.

Section A: Household

A1. How many people are in your household?	Enter a number:	Adult	☐	Children	☐
A2. How many adult in your household are in the age over 65?	Enter a number:		☐		
A3. How many adult in your household are currently employed?	Enter a number		☐		

1

Section B: Appliance Use

Please look at each appliance time of use listed in column 1 and then complete the relevant entry in other columns using √.

Time of Use	Electric Appliance											
	Hob	Elec. Oven	Microwave Oven	TV	Video Recorder	Washing Machine	Tumble Driers	Dishwasher	Kettle	Vacuum Cleaner	computer	Iron
06:00												
06:30												
07:00												
07:30												
08:00												
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Section C: Lighting Use

C1. How many light bulbs in each room are currently used, please enter a number?

Bedrooms	
Kitchen	
Living Room	
Bathroom	
Others	

C2. Please look at the lighting time of use in column 1 and then complete the relevant entry in other columns using √.

Time	Bathroom	Kitchen	Living Room	Bedrooms	Others
06:00					
06:30					
07:00					
07:30					
08:00					
08:30					
09:00					
09:30					
10:00					
10:30					
11:00					
11:30					
12:00					
12:30					
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14:30					
15:00					
15:30					
16:00					
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Thank you for taking the time to complete this questionnaire

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Appendix B

B. 1 List of Author's Publications

The following are publications written by the author in conjunction with others during his PhD candidacy.

B.1. 1 Journal Papers:

[1] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "Statistical predictions of electric load profiles in the UK domestic buildings," *Iraq Journal Electrical and Electronic Engineering,* vol.7 no.2, pp.151-156, 2011.

[2] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "The Generation of Electric Load Profiles in the UK Domestic Buildings Through Statistical Predictions," *Journal of Energy and Power Engineering,* vol.6 no.2, pp.250-258, 2012.

[3] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "Investigation of tariff initiatives for peak load balancing at the domestic level," *Transactions on Systems, Signals and Devices (Issues on Power Electrical Systems),* (Accepted).

[4] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "Optimization of electricity tariffs for peak load balancing at the domestic level," *Journal of Electric Engineering (JEE),* (under review).

B.1. 2 Conference Papers

[1] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "Statistical predictions of electric load profiles in the UK domestic buildings," in *Energy, Power and Control (EPC-IQ), 2010 1st International Conference on*, 2010, pp. 345-350.

[2] A. M. Ihbal, H. S. Rajamani, and M. K. Jalboub, "Electricity load profiling for the Domestic Buildings", *the Libyan Arab International Conference on Electrical and Electronic Engineering (LAICEEE-2010*), Tripoli, October 23-26, 2010.

[3] A. M. Ihbal, H. S. Rajamani, R. A. Abd-Alhameed, and M. K. Jalboub, "The influence of different tariffs schemes on electricity consumption for the UK domestic buildings," in *Systems, Signals and Devices (SSD), 2011 8th International Multi-Conference on*, 2011, pp. 1-6.

B. 2 Selected Author Publications papers

B. 3.1

Journal of Energy and Power Engineering 6 (2012) 250-258

The Generation of Electric Load Profiles in the UK Domestic Buildings through Statistical Predictions

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Abstract: Various forecasting tools exist for planners of national networks that are based on historical data. These are used to make decisions at the national level to meet a countries commitment to CO_2 emission targets. However, at a local community level, the guidance is not easily understood by planners. This work presents for the first time a methodology for the generation of realistic domestic electricity load profiles for different types of UK households for small communities. The work is based on a limited set of data, and has been compared with measurement. Daily load profiles from individual dwelling to community can be predicted using this method. Results have been presented, and discussed.

Key words: Electricity load profile, demand side management, energy consumption, electrical appliances.

1. Introduction

In the UK the domestic sector accounts for almost one third of the total electricity consumption. It contributes the largest peak demand, particularly in the winter season, which has consequences on the power infrastructure [1]. Traditional forecasting methods look at national energy profiles based on historic trends and thereby determining the infrastructure requirements. Recently, energy saving methods, and embedded energy supplies via renewable or combined heat and power, make it possible for local communities to modify their behavior. In this paper, we present the method of examining the energy profiles of small communities that can be easily modified to give reasonable indication of opportunities for bringing in energy conservation into a community.

In order to achieve this, it is necessary to model the local community energy profile based on a reasonable set of data, which can be easily obtained by the energy consultant of the community. A literature review shows that number of surveys and measurements have been done in the domestic energy sector [2-6]. There also have been a number of models proposed [1, 7-11].

A number of data sources have been identified in the literatures that form the basis of such modeling. An energy monitoring campaign was undertaken by Newborough et al. [2]. where the energy demand data of 30 homes were collected in order to compute electricity demand emanating from individual dwellings to reduce the peak demand. A survey of a sample of more than 1000 adults was conducted via a questionnaire in the south east of England in order to collect data on ownership levels of appliances, Usage-patterns, et al. [3]. Other researchers when modeling domestic energy in the UK have used the results of their study.

A measurement of electrical energy consumption profiles for the social sector in the UK, obtained over a period of 2 years, was presented by Kreutzer and Knight [4]. The measurements were all obtained at 5 minute intervals. Annual energy consumptions, daily and overall profiles were derived for the dwellings

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from the data. An occupant survey was undertaken among the people living in the monitored dwellings in order to create a link between the energy consumption profiles and socio-economic factors. The monitored dwellings were categorised on the subject of floor area, number of occupants and ownership level of electrical appliances.

The Swedish Energy Agency recorded appliance consumption data of individual appliances for 400 households in order to understand where and how measures should be taken to increase the number of energy efficient appliances in the homes [5]. The patterns of electricity consumption and how occupancy and housing characteristics affect domestic electricity use for 27 homes in various locations throughout Northern Ireland (city, town and village) were studied [6]. The results of this study showed that there is a strong correlation between average annual electricity consumption and floor area.

Previously, household load profiles have been generated based on detailed information on occupant behavior, and on number and usage of domestic appliances [7]. The model was based on the main factors of occupant availability, their activities and appliance ownership.

A simple method of formulating load profile (SMLP) for UK domestic buildings was presented in Ref. [8]. The input data of the model was based mainly on public reports and statistics, such as the composition of households and average energy consumption of appliances per capita.

Paatero and Lund [9] presented a method for creating domestic electricity load profiles at individual household level. It is a bottom-up model where the household load comprises of individual appliance groups. The input data of the model was based mainly on public reports and statistics.

A generalized tool to assess the response level of domestic consumers to measures is given in Ref. [1]. A method to generate the load profiles for household electricity consumption was presented and the impact of different electricity tariffs was shown.

Armstrong [10] presented a set of three annual non HVAC (Heating, Ventilating, and Air Conditioning) load profiles at five minutes time interval for each of three target Canadian households (low, medium and high energy detached), based on a limited amount of available information [10].

Richardson [11] presented a high resolution model of domestic electricity load profile. This model was based on both of occupancy patterns (when occupants are at home and awake), and profiles of daily activities that describe how occupants spend their time performing certain actions. One minute time interval synthetic electricity load data was generated throughout the simulation of domestic appliances use.

In this paper, a methodology is presented that initially creates a virtual community of households in a small community based on survey of a similar community, and then predicts the energy behavior of each household, and hence of the community.

2. Methodology

The identification of the pattern of energy uses of a house and the prediction domestic load profile is an essential in order to match load shape to the power generated, and also to predict the possible impact of any energy management action directly on the daily load profile.

The electrical load profile is based on assumptions as to the type of electric devices including appliances and lighting, and their usage. Different households have different lifestyles, which mean the shape of the total load profile will fluctuate from house to house, and from day to day.

2.1 Primary Data Sources

The inputs of the electricity demand profile generator being presented here are:

• Demographic information: The information on the type of households is required such as the number of adults, working people, and number of children;

• Annual electricity consumption patterns: Includes ownership level of appliances, and total energy consumption of certain appliances;

• Daily occupancy information: This is the behaviour of occupants in households with respect to their usage of appliances and lighting on a daily basis.

2.1.1 Demographic Information Required

The census data available at the UK Office for National Statistics (ONS) is used as the primary information [12]. The UK had a population of 61 million in 2008 and a total of 25 million households with an increase of almost 0.6 per cent on 2006. The average household size is 2.4. Table 1 shows the household composition in 2008 by the type of households [12]. The largest component is the two adult households with no children constituting 24%.

For this generator, we have chosen to use household types as scenarios for prediction.

2.1.2 Annual Electricity Consumption Patterns

The information of the average daily consumption for major appliances in the UK household is obtained from Mansouri [3], who carried out a survey. The information gives the type and the average annual consumption per household per day, the average annual consumption per capita per day and the ownership level. Table 2 lists the average energy consumption of appliances in the UK. The consumption is given by households as well as by per capita. The ownership levels are also presented by household.

Fig. 1 shows the ownership level of domestic appliances in the UK. This information is obtained from Ref. [3], and was updated using data from the Department for Environment Food and Rural Affairs (DEFRA) [13]. The tags marked by "*" are the updated ones.

2.1.3 Daily Occupancy Information

The daily occupancy information available in literature is limited, so simpler assumptions have been made for each scenario. Although the demand for cold appliances normally varies during the duty cycle of the appliance, the assumption of constant load is assumed sufficiently accurate [14], the remaining appliances will

Table 1 Household type.

Type of household	Percentage share (%)
Single adult without children	15
Single adult with children	6
Single retired adult	15
Two adults without children	24
Two adults with children	19
Two retired	9
Two adults or more without children	8
Two adults or more with children	4
Total	100

Table 2 Average energy consumption of electrical appliances in the UK [3].

Appliance	Average annual consumption per household (kWh/day)	Average annual consumption per capita (kWh/day)
Electric hob	1.33	0.39
Electric oven	0.74	0.22
Microwave oven	0.23	0.07
Refrigerator	0.82	0.33
Freezer	1.9	0.55
Television	0.91	0.27
Video recorder	0.3	0.09
Dishwasher	1.72	0.48
Washing machine	0.8	0.2
Tumble driers	0.78	0.28
Electric kettle	0.78	0.28
Iron	0.3	0.09
Vacuum cleaner	0.15	0.04
Miscellaneous	1.1	0.33
Computers	0.5	0.3

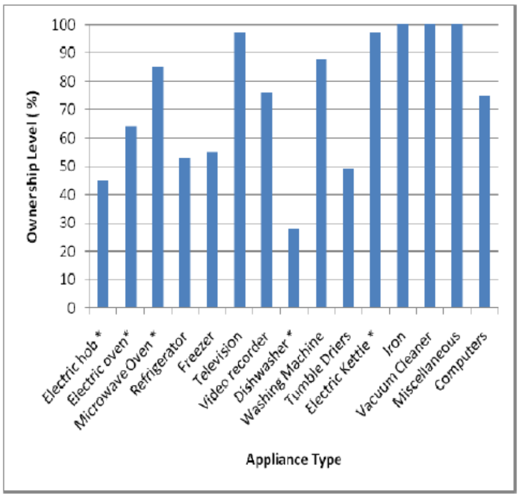

Fig. 1 Ownership level of domestic appliances.

have discrete events where the appliance is switched on and utilized. A questionnaire was designed for this purpose.

The objective of the questionnaire was to collect specific data to find out when and how many occupants switch on electrical appliance in different times of the day. The results of the survey will help us to get probabilistic estimates of usage of electrical household appliances. The questionnaire contained two sections. The first requests general information about the household to give an overview of provision household type and occupancy patterns. The second section requests general information about the use of electric appliances to collect specific data on when and how many do occupants switch on electrical appliance at different times of the day.

The questionnaire survey was distributed among 86 household in the BD7 area in Bradford. The results are discussed later.

Due to the lack of household occupancy pattern information, it is necessary to make assumptions for the most common scenarios of household occupancy pattern in the UK. Eight scenarios of occupancy pattern have been assumed according to household type given in Table 3.

2.1.4 Daily Energy Consumption of Appliances

The daily energy consumption of electrical appliances for different types of household can be calculated based on average annual consumption per day (per capita or per household depending on the scenario). In order to generate appliances load profile the following assumptions have been made:

- Each household has only one of each appliance listed above;
- The weekend hourly load curves have been equalized to those for the workdays for calculation simplicity;
- The heating and hot water systems are provided by means of natural gas. Although the boiler uses electric powered burner, the electric consumption of this burner is too small and has not been considered.

2.2 Electric Lighting Patterns

The electric light depends on the occupancy pattern and is highly affected by daylight condition (season) and the presence of active occupants, e.g, in winter, people need to switch on the artificial lighting in the morning for the activities but in summer due to the daylight no artificial lighting required. The following equation can be used to calculate the electric lighting energy consumption (E_l):

$$E_l = N_b \times E_{rb} \qquad (1)$$

where N_b is the number of light bulbs per household distributed between bedrooms, kitchen, living room, bathrooms and others and E_{rb} is the energy rating per bulb per hour.

3. Generating the Profile

3.1 An Area of Study

In this study, we are generating a load profile for an assumed community of 400 households.

3.2 Household Type Allocation

To get a picture of the demographic characteristics of the area in order to allocate different numbers of households, calculation was based on the percentage share of UK household (Table 1). Fig. 2 shows the projected number of households of the assumed community.

The physical location of the households was then allocated randomly using Excel's rand function.

3.3 Ownership of Appliances Allocation

The appliances are physically allocated to households based on the national ownership level (Fig. 2) and using the random function.

3.4 Time of Use Probability Profiles

Fig. 3 shows the probability of first usage times per day for electric hob for the single adult household that resulted from questionnaire survey analysis. This data is obtained from the questionnaire survey of BD7. In

Table 3 Scenarios profiled & occupancy assumptions.

Scenario	Household type	Unoccupied period & assumptions
1	One working adult	08:30 to 18:00
2	One retired	House is occupied all the time.
3	One adult with children	08:30 to 13:30, the occupier is a part time working.
4	Two working adults	08:30 to 18:00
5	Two working adults with children	08:30 to 13:30, one adult has full time job. Other may have a part time job in morning to take care of the children after school.
6	Two retired	House is occupied all the time.
7	Three adults or more	13:00 to 18:00, two members have full time job; the other has a part time job in the afternoon.
8	Three adults with children	The house is occupied all the time, two adults have a full time job and the other one is retired.

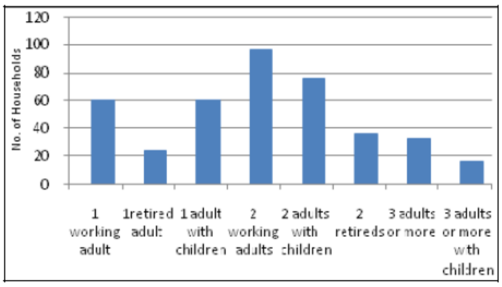

Fig. 2 Projected numbers of households.

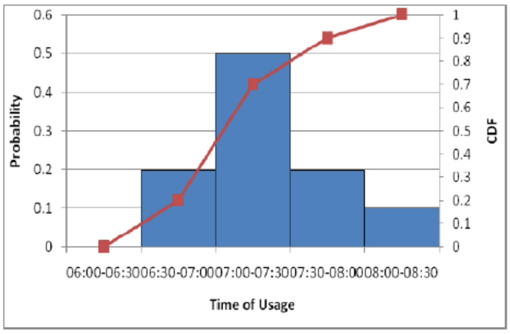

Fig. 3 Probability & cumulative distributive function of first usage times per day for the hob for the single adult household.

other words the behavior is being predicted on the basis on a particular community. Hence, the assumption is that the 400 household community has similar behavior with respect to appliances as the BD7 community. Similar graphs for other appliances and types of households have been obtained via the survey. The graph (Fig. 3) is used to allocate the time usage for the single adult households who have already been allocated an electric hob.

For lighting, the winter and summer aspects are included in the modeling. For other appliances the assumption is that the behavior is the same.

3.5 Electricity Demand Profile Generator

The random profile generator is implemented in Excel at half hourly basis in order to generate electrical load profiles. Fig. 4 shows the outline of the generator.

The number of households in the community is the initial input. The number of household types is then calculated using external data from the UK national statistics giving the composition of households. The household type is then distributed in the community in a random manner reflecting the reality of a community. The appliances for household types are then determined using external data on ownership levels. The appliances are then distributed again in a random

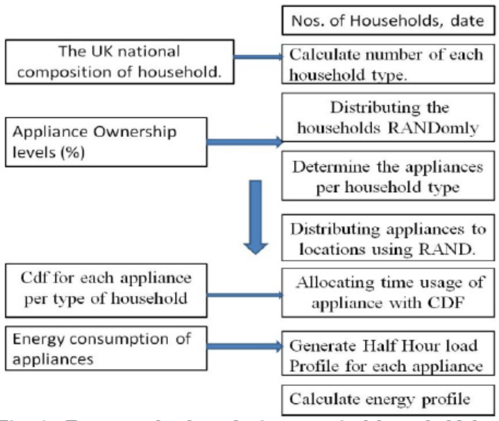

Fig. 4 Framework of producing a typical household load profile.

manner. The time usage of each appliance is then predicted using the cumulative distributive function that was previously determined by survey of a similar community BD7 Bradford. Finally the energy consumption of each appliance from external data base is included so that the total energy consumption can then be computed. The summation of the whole community can then be done to determine the community load profile.

4. Results

As an example of the functioning of the load profile generator, typical half hourly load profiles have been generated for the community that was used in this study. Various results have been obtained. In this paper we submit some results of interest.

The energy profiles of the eight scenarios of households have been produced and the averages are calculated for each household type and plotted in Fig. 5. Note that the random nature implies that results are only particular to the instant.

All except scenarios 2 and 6 show the typical small peak in the morning and a significant peak in the evening. The reasons for this are that the two scenarios are about retired people. Typically they have high energy consumption during the daytime. In scenario 5, a third peak is visible in the afternoon as one of the occupants has a part-time job so as to return from work to take care of children returning from school. Scenarios 3, 4, 5, 7 and 8 show similar magnitude of energy consumption despite different occupancy.

Fig. 6 shows the energy consumption of the whole community giving the maximum, average and minimum daily possible values. This was done by running the profile for 23 runs (i.e. random days). The two adults with children households and the two working adults households contribute to the most energy consumption which accounts for about 28% and 21% of total domestic energy consumption respectively.

Fig. 7 shows the total daily energy consumption in the particular community of 400 households. The energy usage in the early morning period is very low as would be expected due to few electric appliances being on. The initial peak of about 120 kWh occurs at around 8:00 hrs when breakfast occurs. The energy consumed then remains almost level at 50 kWh with only a slight increase as children return from school. After 17:00 hrs, there is a significant increase in consumption as people return home. This remains high until around 21:00 hrs when it starts falling. The maximum and minimum are seen to be significant in the evening period varying by 15% at the highest peak.

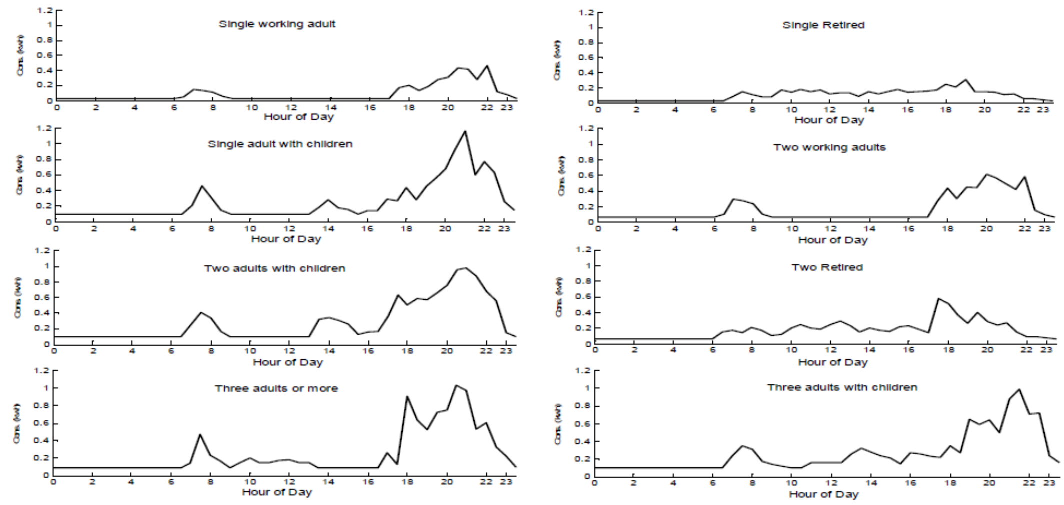

Fig. 5 Half-hourly average daily consumption for eight scenarios.

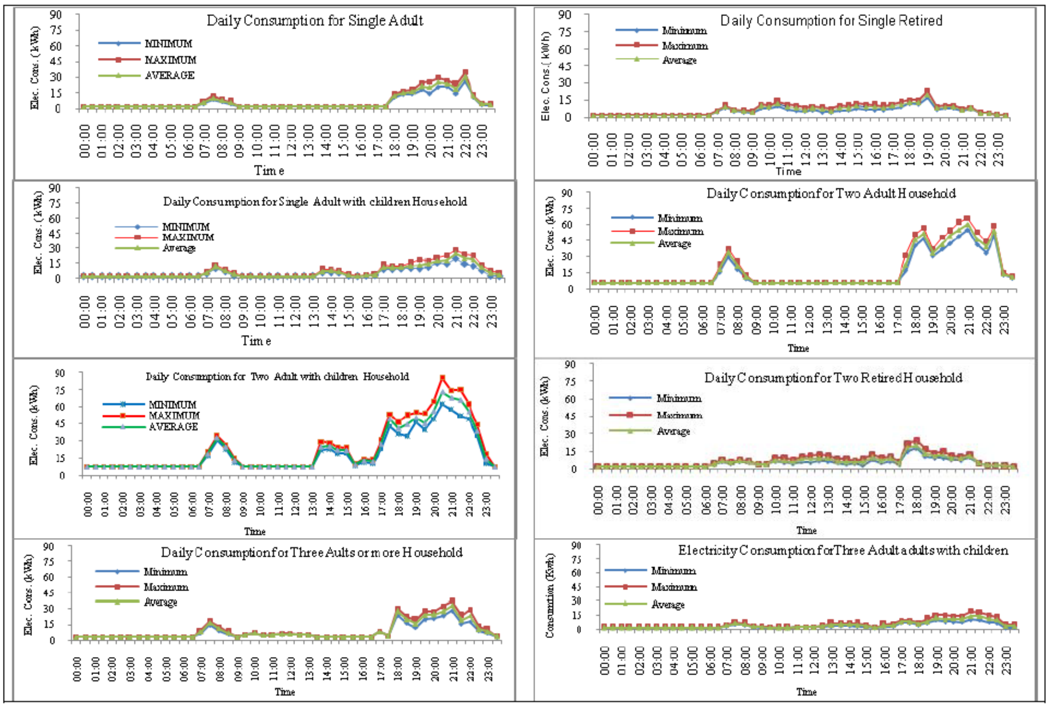

Fig. 6 Daily maximum, average and minimum consumption in community (for above groups).

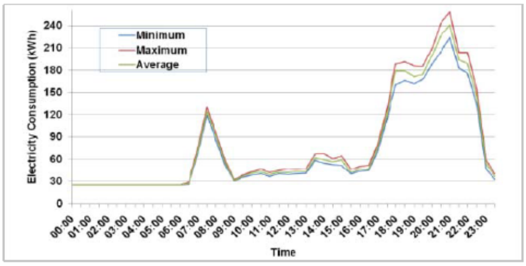

Fig. 7 Total energy consumption profile of the 400 household community.

5. Comparison to Measured Data

A typical English terraced three storeys house with a total floor area of about 100 m^2 was selected for the electricity consumption monitoring. The number of occupants in the house is six (two adult and four children who are of school age). One of the adult is a full time student, the other one is a part time working in the morning period in order to take care of the children after school.

The monitoring took place during the period January 2010 to December 2010 in BD7 area in Bradford, in Northern England. This is the same location where the survey was conducted. The house space heating, domestic hot water (DHW) and cooker have been provided by means of gas. The total electricity consumption has been measured and monitored at a high resolution (1 min interval). The data were collected by using OWL Wireless Energy Monitor which enabled remote downloading of stored electricity consumption in kWh during one minute interval. The data are transmitted periodically to a computer via a USB receiver and displayed using OWL Home Energy Monitor program. The collected data are exported as a CSV file that can be opened up with spreadsheet type applications. The data presented are for one complete year and enclosed over 400,000 individual data values. The daily load profiles logged at 1 minute interval are averaged over 30 min time interval (this has been done in Microsoft Excel spreadsheet).

Fig. 8 shows the measured data from the household compared with one predicted by the profile generator. The averaged half hourly load profile from the measured data has shown a reasonable agreement compared with the generated load profile for the same household type (i.e., scenario 5; two adult with children household). The average daily electricity consumption from the measured data is about 9 kWh, and about 11 kWh from the generated load profile for the same household type. The profile from monitored data is slightly lower than the generated profile because the cooker have been provided by means of gas and the household does not have some appliances such as dishwasher and tumble dryer.

It can be seen that the base load of the demand occurs overnight and is mainly from cold appliances, continuous appliances and appliances in standby mode. The initial peak occurs between 6:30 hrs and 8:30 hrs. The second peak occurs between 13:30 hrs and 15:30 hrs as one of the occupants returns to take care of the children. Finally, the peak in the evening occurs as the family returns.

The significant difference that occurs after 21:00 hrs indicates that the occupants of the household do not reflect the typical behavior of British households. This is verified to be true as the nationality of the occupant is non-British.

6. Discussion

The results are primarily based on a combination of the statistical data, and a survey. The higher the accuracy required, the more detailed the two input streams would have to be. In this example, the survey was done with only sixty two participants. With this information, it was possible to profile a "similar" community of four hundred. For a community that may be different from this, we would require the survey to be conducted in a community similar.

The results show which category of household contribute most to the peak. It is possible therefore to focus energy conservation to those households first

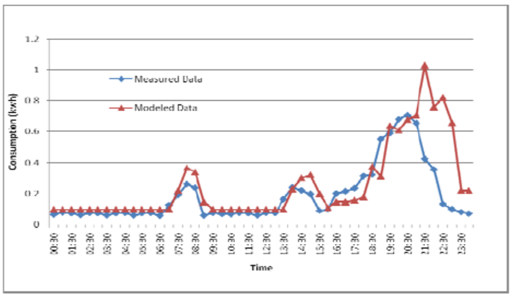

Fig. 8 Comparison of modelled load profile to measured data.

rather than the whole community which may be too costly. This feature of the tool is useful to consultants.

The variations in the daily usage between maximum and minimum indicate that there must be opportunities for behavior change with respect to time of use so as to result in less peak demand.

As the energy demand is definitely at peak evening period, the feasibility of introducing renewable energy must be considered with respect to evening operation. As such this naturally excludes photovoltaic unless significant storage is provided with the photovoltaic. This analysis using the tool is suggested before any energy technologies are introduced into a community.

7. Conclusions

A generation tool to predict electricity energy scenarios for small local communities has been presented for the first time to help local planners decide on measures such embedding renewable energy and demand management. This is in contrast to powerful national prediction tools able to give overview and remaining out of reach of local planners.

The inputs are based on a limited set of statistical data of household types, and of ownership levels, both of which are available in the public domain.

The scenarios are made relevant to the communities being investigated by carrying out a straightforward survey of consumer behavior in similar communities.

The differences between eight types of households show that occupancy has a significant impact on energy consumed. Local planners could modify this, if their community household differs from national, to help plan for their communities.

The tool has been compared with measurements of a single household, and shows reasonable agreement.

Type of building could be incorporated into the tool so that scenarios involving incentives of building stock could be studied.

8. Future Work

The tool has been used to study measures that could be used to reduce energy consumption. The results will be published when available.

The tool is also being used to carry out an investigation into the possible influence of different tariff schemes on consumer behaviours in UK domestic buildings.

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B. 2.2

2011 8th International Multi-Conference on Systems, Signals & Devices

THE INFLUENCE OF DIFFERENT TARIFFS SCHEMES ON ELECTRICITY CONSUMPTION FOR THE UK DOMESTIC BUILDINGS

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ABSTRACT

Electricity Suppliers in competitive electricity markets commonly respond to prices changes which are fluctuating over time, but most consumers respond to the price changes as reflected on their electricity bills. Almost all consumers pay fixed tariffs for their consumption without distinctions based on usage time, so these consumers have had no incentives to reduce their use during the peak times. This paper aims to analyze the influence of different tariff schemes on consumer behaviours in UK domestic buildings. A realistic half hourly electricity load profile for different types of UK households that based mainly on public reports and statistics has been generated. This load profile data were used to help calculate the expected change in consumers' bills under standard tariffs offered from different suppliers to what the cost of electricity would be under time varying tariff (economy7 tariff) and to estimate of how much consumers would shift their load in response to price changes without changing total consumption, for which the results are presented and discussed..

Index Terms— Tariff, electricity consumption, load profile

1. INTRODUCTION

The recognition of the pattern of energy uses of a house and the prediction of domestic load profile is a vital in order to match load shape to power generated, and also to predict the possible impact of any energy management action directly on the daily load profile. The usage of electrical appliances is associated to the occupancy period. The total energy load profile can vary significantly from time to time depending on number of occupants, their behaviours and the unoccupied period during the day. In the UK the domestic sector is accountable for almost one third of the total electricity consumption. It contributes the largest peak demand in winter season, which is hurting the available power infrastructure, and meeting the peak demands in winter is progressively more costly and high price spikes is seen [1]. The domestic energy consumption in the UK can be divided into three categories: space heating, domestic hot water, lighting and appliance. The usage pattern varies depending on many determinants, such as weather, household composition, income, behaviour patterns of occupants; etc. The consumption per time interval is the sum of many consuming appliances. The load of a typical appliance connected to the grid is fluctuating over time and depending on time of usage. This results in a fluctuating electricity demand during a day and during a week.

Under competitive electricity markets condition, if rational electricity tariff to consumers is determined, consumers could be encouraged to modify style of their consumption in response of financial incentives. Consequently we can achieve the objective of making load in a more steady level and recovering the stability and efficiency of the power system. As one of power prices to consumers, TOU electricity tariff is extensively applied in many countries. Furthermore, it is one of significant tools of demand side management (DSM) which encourage consumers to adjust their consumption during the high demand periods [2]. Time varying tariffs offer smart off peak rates, but relatively high peak rates. TOU tariffs for domestic consumers were first begun in 1965 and led to a exceptionally significant growth of electric storage water heaters and the resultant growth of off -peak consumption [3]. In the UK; Economy 7 is the familiar scheme for domestic consumers. It is a cheaper night time electricity tariff which normally operates from midnight where seven hours of low tariff electricity at night.

For a Time varying tariffs to be valuable, advanced metering infrastructure (AMI) which carries capability to display real time prices .The availability of such information will allow consumers to respond o the variant in electricity tariffs. This is generally known as demand response [4].

There have been numerous investigations dealing with domestic electricity consumptions load profiles and electricity prices in the UK [5-12]. A monitoring campaign was undertaken by Newborough [5] where the energy demand data of 30 homes have been collected in order to modulate electricity demand emanating from individual dwellings to reduce the peak demand. A survey data among a sample of more than 1000 adults has been conducted and a questionnaire was designed in the south-east of England in order to collect information from consumers about environment, Ownership of appliances, Usage-patterns, and etc [6]. The result of this study, such as ownership level, and total energy consumption of

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certain appliances are generally used when modeling of domestic energy is carried out for the UK. A simple method of formulating load profile (SMLP) for UK domestic buildings was presented by R. Yao and K.A. Steemers [7]. The input data of the model was based mainly on public reports and statistics, such as the composition of households and average energy consumption of appliances per capita. The UK average size household (3 persons) was selected as an example of the implication of this method.

Paatero and Lund [8] presented a method for creating domestic electricity load profiles at individual household level. It is based on a bottom-up model where the household load composes individual appliances/appliance groups. The input data of the model was based mainly on public reports and statistics. V.Hamidi and F. Li [9] presented a generalized tool to assess the responsiveness level among domestic consumers by studying load profiles for different domestic consumers which are composed of power consumption of end-use appliances and also showed the impact of different electricity tariffs on the load profile of domestic consumers. A 1992 study was carried out by the Electric Association in the U.K. stated the most of consumers favoured a TOU tariff, and modified their energy usage. As likely, energy usage was reallocated to the less costly off peak period, while the whole monthly consumption remained reasonably constant [10].

This paper focuses on generation of different households load profiles in the UK domestic buildings and shows the impact of different electricity tariffs on consumers' behaviours.

2. HOUSEHOLD AND PROFILES

The UK has a population of 61 million in 2008 and a total of 25 million households with an increase of almost 0.6 per cent on 2006. Since 1971 the population has increased by 5.0 million. The average household size is 2.4.

A realistic half hourly electricity load profile data for the UK domestic buildings excluding the heating and hot water systems has been generated. The space heating and hot water systems are assumed to be provided by means of natural gas.

This profile is based on the information and results of previous investigations and works that is available in public reports and statistics. The produced electrical load profile is based on engineering assumptions as to the type of appliances owned and lighting that are in the house and when the occupants are likely to switch them on. The different households have different lifestyle; consequently, the shape of total load profile will fluctuate from house to house and day to day. The inputs of electricity demand profile generator are:

- The Census Demographic data which available from the UK Office for National Statistics (ONS) [11].
- Average annual electricity consumption of certain appliances (kwh/day per capita or household) and ownership level of appliances [6].

Table 1 list the type of households in the UK for the year 2008 [11] and table 2 lists the average energy consumption of appliances in the UK [6, 12].

Due to lack of information about occupancy pattern of households, eight scenarios which present the most common scenarios of household occupancy pattern in the UK were proposed based mainly on public reports, statistics and questionnaire data in order to generate realistic load profile for different consumers.

Table 1.Type of households

Type of Household	Percentage Share (%)
Single adult without children	15
Single adult with children	6
Single retired adult	15
Two adults without children	24
Two adults with children	19
Two retired	9
3 adults or more without children	8
3 adults or more with children	4
Total	100

Table 2. Average energy consumption of electrical appliances in the UK [6, 12]

Appliance	Av. Annual Cons. Per Household (kwh/day)	Av. Annual Cons. Per Capita (kwh/day)	Ownership level
Electric hob	1 33	0.39	55*
Electric oven	0.74	0 22	64*
Microwave oven	0 23	0 07	74
Refrigerator	0 82	0.33	53
Freezer	1.9	0.55	55
Fridge-freezer	1.9	0.56	58
television	0.91	0.27	97
Video recorder	0 3	0.09	76
dishwasher	1.72	0.48	16
W/Machine	0.8	0.2	88
Tumble dryer	0.78	0.28	49
Electric Kettle	0.78	0.28	97*
Iron	0.3	0.09	100
V. cleaner	0 15	0 04	100
Miscellaneous	1 1	0.33	100
Computers	0.5	0 3	75

2.1. Time of Use Probability Profiles

In order to create sensible load profiles, knowledge of occupancy patterns is required. The occupancy information was limited, so simpler assumptions have been made for each scenario. Although the demand for cold appliances normally varies during the duty cycle of the appliance, the assumption of constant load is assumed to be sufficiently accurate [13], the remaining appliances will have discrete events where the appliance is switched on and utilised. The usage time and probability of occurrence of each appliance was distributed randomly based on the occupancy period. The time of use probability is determined based on the questionnaire data survey analysis for a case study region. Figure1 shows the probability of first usage times per day for electric hob for the single adult household that resulted from questionnaire survey analysis. The lighting load was dealt separately.

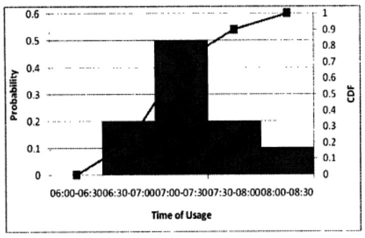

Figure 1. Probability of first usage times per day for the hob for the single adult household.

Table 3. lists the most eight scenarios of likely occupancy period in the UK houses.

Table 3. Most common scenarios of likely occupancy period in the UK houses

Scenario	Household Type	Unoccupied Period
1	single working adult	08:30 to 18:00
2	Single retired adult	The house is occupied all the time
3	Single adult with children	08:30 to 13:30
4	Two working adults	08.30 to 18.00
5	Two adults with children	08.30 to 13.00 `-
6	Two retired	house is occupied all the time
7	Three adults or more without children	13:00 to 18:00
8	Three adult household with children, one occupant is retired.	The house is occupied all the time

2.2. Electricity Demand Profile Generator

A random profile of each individual appliance for each scenario was generated using Excel random profile generator which based on probability that enable us to predict the possibility of each consumer to run a number of appliances on a certain time of the day for different occupancy scenarios by describing the behaviour of each appliance which based on a probability between (0& 1). The usage time and probability of occurrence of each appliance was distributed randomly based on the occupancy period. The aggregation of the whole random profiles for all appliances will generate a daily consumption load profile for a known scenario. Fig 2 shows the framework of generating a typical single household load profiles.

The daily energy consumed by each appliance is calculated using one of the following equations:

$$E_a = N \times \sum E_{apc} \tag{1}$$

$$E_a = \sum E_{aph} \tag{2}$$

Where E_a is the daily energy consumption of household delivered by appliances; N is the number of occupants, E_{apc} is the appliance energy consumption per capita and E_{aph} is the appliance energy consumption per household.

The load profile for the whole community was calculated using the equation:

$$Load_{community} = \sum_{j=1}^{8} E_{aj} \tag{3}$$

Where; $Load_{community}$ is the load profile for the whole community; E_{aj} is the half hourly load profile of household of type j.

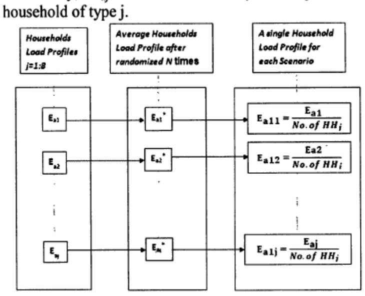

Figure 2. Framework of producing a typical single household load profile

The average load profile for a single household for the whole community (eight scenarios together) is calculated by averaging the summation of the averages of all scenarios. The modeling results for the whole scenarios are shown in Fig 3.

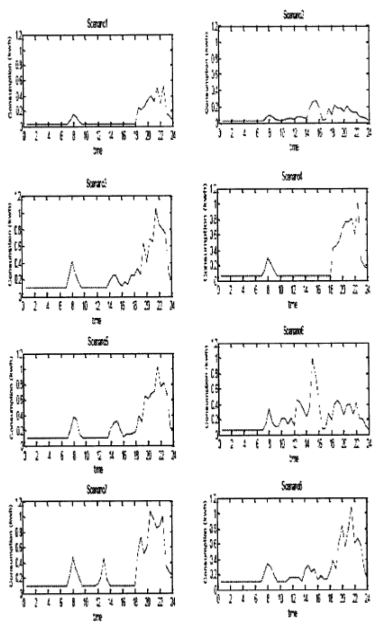

Figure 3. Average half-hourly daily consumption for the whole scenarios

3. TARIFFS STRUCTURES

The consumers can help a utility by means of demand side management program if they are offered the right incentives.

Today in UK, most consumers have charged at standard electricity tariff for their consumption regardless of time of use. The standard tariff has currently two types: Standing charge tariffs and two tier tariffs. On the other hand, many UK suppliers have provided Economy 7 tariff. Economy 7 tariff is a cheaper night time electricity tariff which normally operates from midnight where seven hours of low tariff electricity at night. During the night period, electricity costs lower than the standard daytime tariff. To shift more energy consumption into the night, some main appliances such as, washing machines, tumble dryers, kettles or dishwasher cycle, electric boilers and heater might be configured to run during the night period tariff.

To examine the consumer's behavior in response to the tariff changes, consumer's quarterly electricity bill under different electricity tariffs schemes offered by five suppliers in the UK is calculated. Tables 4 list the standard tariffs plans offered by five suppliers (Source: http://www.ukpower.co.uk/home_energy/compare_electricity, on 9th Jul 2010) and tables 5 lists the economy 7 tariff offered by one of the five suppliers [15].

Table 4. Economy 7 electricity tariffs by Sainsburys energy supplier

Brand	Rate
Band A (1000 kWh each year)	23.8p
Band B kW	11.21p
Night kWh	5.03p

Table 5. Standard electricity tariffs offered by five suppliers

	npower	Atlantic Electric& Gas	Sainsburys Energy	British Gas	Scottish Power
Standing Charge	0	8.4210 p a day or 7.68per quarter inc. VAT	0	0	13.301 p a day or 12.14per quarter inc. VAT
Tier 1	14.91p kwh for the first 728kwh inc. VAT	11.885 p kwh inc. VAT	19.91p kwh for the first 900kwh inc. VAT	23.5380p kwh for the first 500 kwh inc. VAT	10.2250 p kwh inc. VAT
Tier 2	13.90p kwh for the rest inc. VAT	0	9.84p kwh for the rest inc. VAT	9.172p kwh for the rest inc. VAT	0

The Band A day rate will apply to a block of 1000 kWh each year (e.g. for an electricity bill covering three months the first 247 kWh will be charged at the band A rate, all extra day kWh will be charged at the band B rate). Night consumption will be supplied for a total of 7 hours between 10pm and 8am (actual times set by the local network operator) and these will be charged off the night kWh rate.

4. RESULT ANALYSIS AND DISCUSSION

A typical half hourly load profiles for UK households for different household types have been generated using statistical method. The daily energy consumption load profiles of electric appliances and lighting loads have been generated individually.

The average half hourly daily energy consumption of a each household type (scenario) is obtained by aggregating the electricity consumed by appliances and lighting at a specific time. The average magnitude of electricity consumption at 30 min intervals of a typical day for each household type was sought. These averages reflect the typical daily consumption for a given scenario. With availability of these results, different scenarios of consumer's bill under standard tariffs offered from different suppliers and economy 7 tariff were calculated in order to understand the benefits of economy7 tariff plan by changing the level of load shifts. due to consumers need to understand more about standard electricity tariff before choosing their suppliers, a comparison between electricity bills for different consumers under standard tariffs offered by five suppliers has been made. Fig 4 shows how different standard tariff plans would affect consumers of choosing their suppliers, e.g if the consumer in scenario 7 is being supplied by the first supplier. So, £30 (19%) would be saved in his quarterly bill if he transfers his supply to fourth supplier.

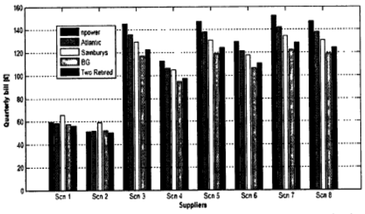

Figure 4. Quarterly consumers' bills using different standard tariff plans from different suppliers for the whole scenarios

The electricity bills under a proposed demand side management by configurating some main appliances such as, washing machines, tumble dryers, kettles or dishwasher cycle, electric boilers and heater to run during night tariff period were calculated. The proposed percentage of the load shifted to night period is ranged from 10% to 50% without changing the total daily consumption. The percentage savings in quarterly consumer's bill using economy 7 tariff compared to standard tariff is listed in table 6.

Table 6. Percentage savings in quarterly consumer's bill using economy 7 tariff compared to standard tariff

%of load shifted to night period	Scenarios							
	1	2	3	4	5	6	7	8
	% Saving							
0	-17.9	-17.8	-10.9	-16.9	-11.1	-13.8	-11.0	-11.0
10	-16.7	-16.5	-7.6	-14.4	-7.7	-11.0	-7.7	-7.6
15	-16.1	-15.9	-6.0	-13.2	-6.1	-9.5	-6.0	-5.9
20	-15.4	-15.3	-4.3	-11.9	-4.4	-8.1	-4.3	-4.2
25	-14.8	-14.6	-2.7	-10.7	-2.7	-6.7	-2.7	-2.5
30	-14.2	-14.0	-1.0	-9.4	-1.1	-5.2	-1.0	-0.8
35	-13.6	-13.4	0.6	-8.2	0.6	-3.8	0.7	0.9
40	-13.0	-12.7	2.2	-7.0	2.2	-2.4	2.4	2.6
45	-12.3	-12.1	3.9	-5.7	3.9	-1.0	4.0	4.2
50	-11.7	-11.4	5.5	-4.5	5.6	0.5	5.7	5.9

As shown from table 6, the difference between consumer's e bill under standard tariff and the expected economy7 tariff bill was calculated for each household type (scenario). Positive difference indicates that the expected economy7 tariff bill would be lower than the actual standard tariff and thus indicates that the household is not expected to benefit under the new economy7 tariff. Similarly, negative differences indicate that the expected bill under economy7 tariff would be less than the actual tiered costs, and thus the household would be expected to benefit naturally under the economy7 tariff. The single household consumers who have small power consumption (scenarios 1,2 and 4) do not appear to benefit from adopting economy 7 tariff, as a result of that economy7 tariff can only be adopted for scenarios 3,5,6,7 and 8. From fig 5 it can be seen that with load shifting of 35%, economy 7 tariff can be adopted only if the daily consumption is about 11.5kwh and that with load shifting of 50%, economy 7 tariff can be adopted only if the daily consumption is nearly to 9 kwh.

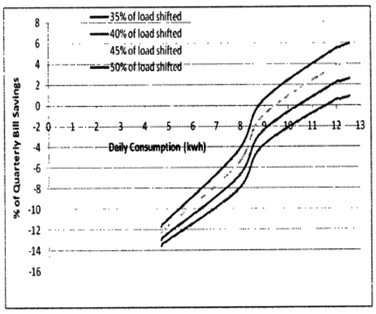

Figure 5. Relation between consumed load and bill savings using different percentage of load shifting

The percentage savings in quarterly consumer's bill using economy 7 are shown in Table 7.

Table 7. Percentage savings in quarterly consumer's bill using economy 7

% of load shifted to night period	Scenarios					
	3	4	5	6	7	8
	% Saving					
0	0.0	0.0	0.0	0.0	0.0	0.0
10	3.0	2.5	3.0	2.1	3.0	3.1
15	4.5	3.8	4.4	3.2	4.5	4.6
20	6.0	5.0	5.9	4.3	6.0	6.1
25	7.5	6.3	7.4	5.3	7.5	7.6
30	9.0	7.5	8.9	6.4	9.0	9.2
35	10.5	8.8	10.4	7.4	10.5	10.7
40	12.0	10.0	11.9	8.5	12.0	12.2
45	13.5	11.3	13.3	9.6	13.5	13.7
50	15.0	12.6	14.8	10.6	15.0	15.3

5. CONCLUSIONS

In this paper the Influence of the changes in electricity tariffs on electricity consumption have been presented. A realistic half hourly electricity load profile for different types of UK households that based mainly on public reports and statistics has been generated. The generated load profile has shown a reasonable agreement compared with the typical national load profile.

From the results it is shown that with elegant demand management (DM) and adopting economy7 tariff, the peak load can be modified to a suitable level to alleviate the insufficient of power supply. Moreover, consumers' bills can be reduced which would support them to adopt time varying tariffs without excessive discomfort to the consumer.

However, the savings depend mainly on some factors such as tariff structure and the load characteristics of the consumers. The consumers who have small power consumption don not appear to benefit from adopting economy 7 tariff. It can be seen by shifting the load to night tariff period, from 13 to 15 percent can be saved in the bill. The consumers need to understand more about their energy usage before making a precise decision about tariffs; as well they should understand the influence diverse schemes might have on behavior. The analysis helps to determine the suitability of adopting demand response in the domestic sector.

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Appendix C

Explanation of algorithm

C. 1 Outline of how to produce households load profiles

Figure C.1 shows the outline of the load profile generator. From the figure, it can be seen that the main inputs are the local community data (number of households) and appliances data in the community is the initial input.

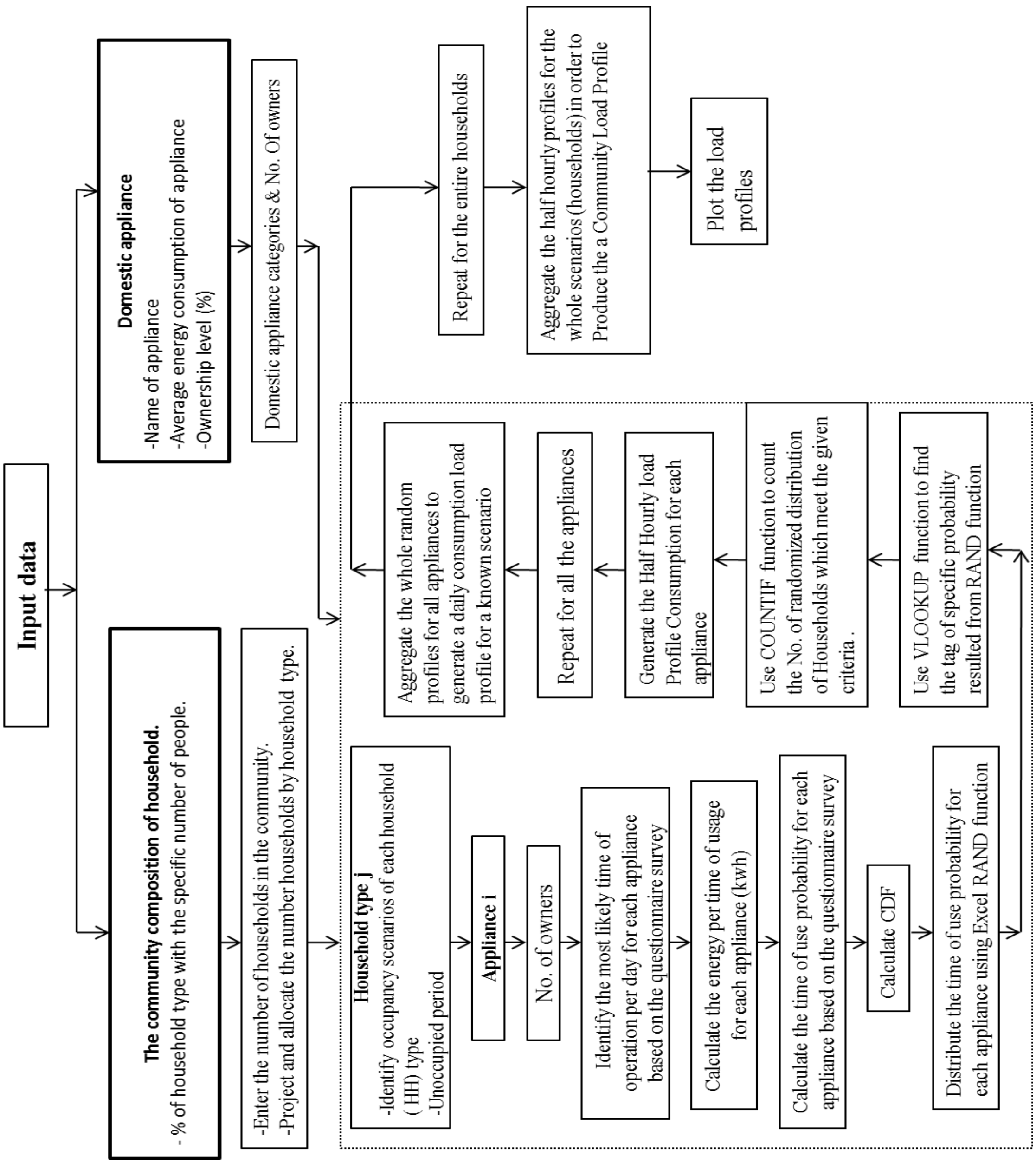

Figure C. 1 Outlines of load profile generation

C. 2 Screen Dumps of the key screens

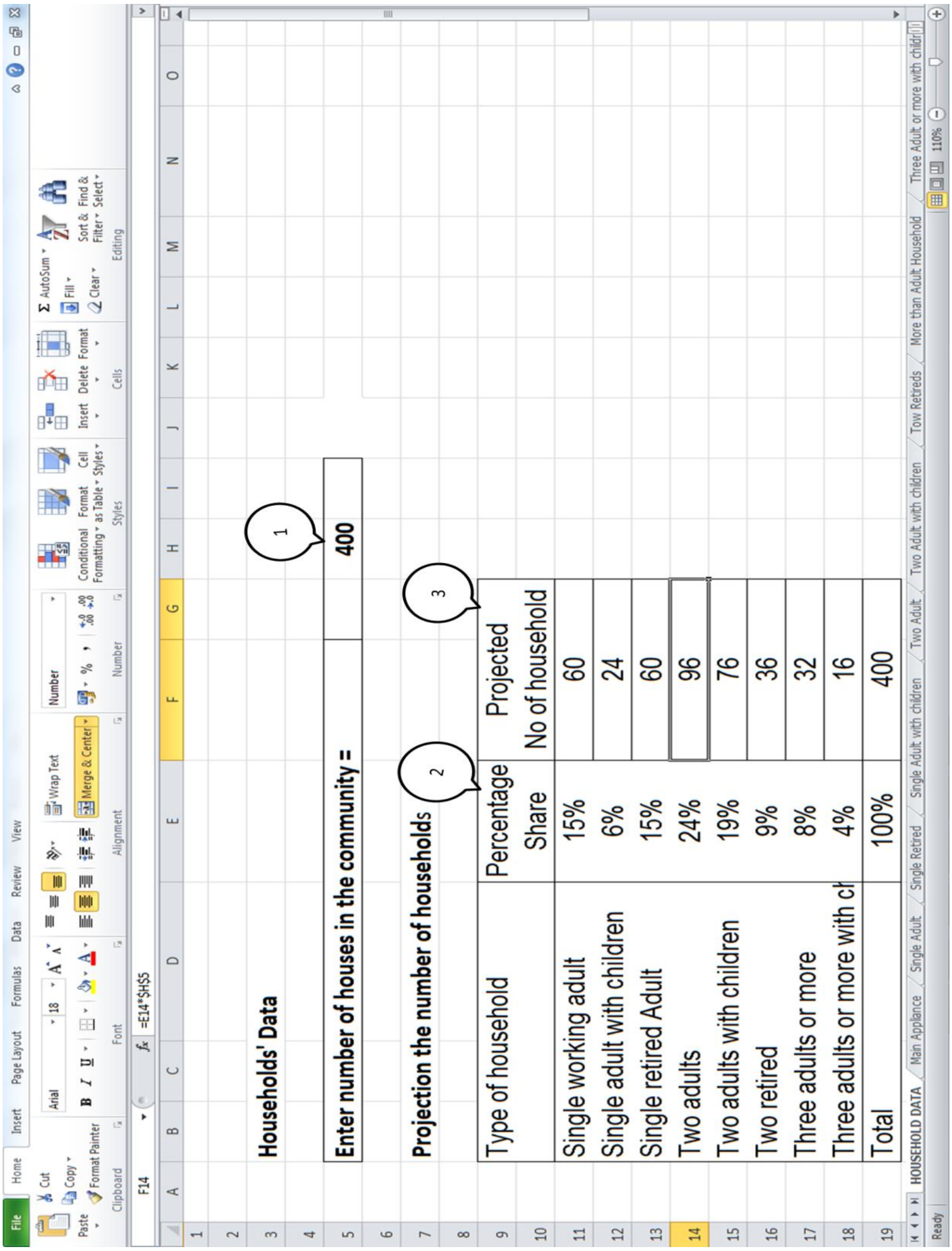

Figure C. 2 Households Data

1. Enter number of households in the community.
2. Calculate percentage share of household type based on questionnaire survey
3. Calculate number of each household type.

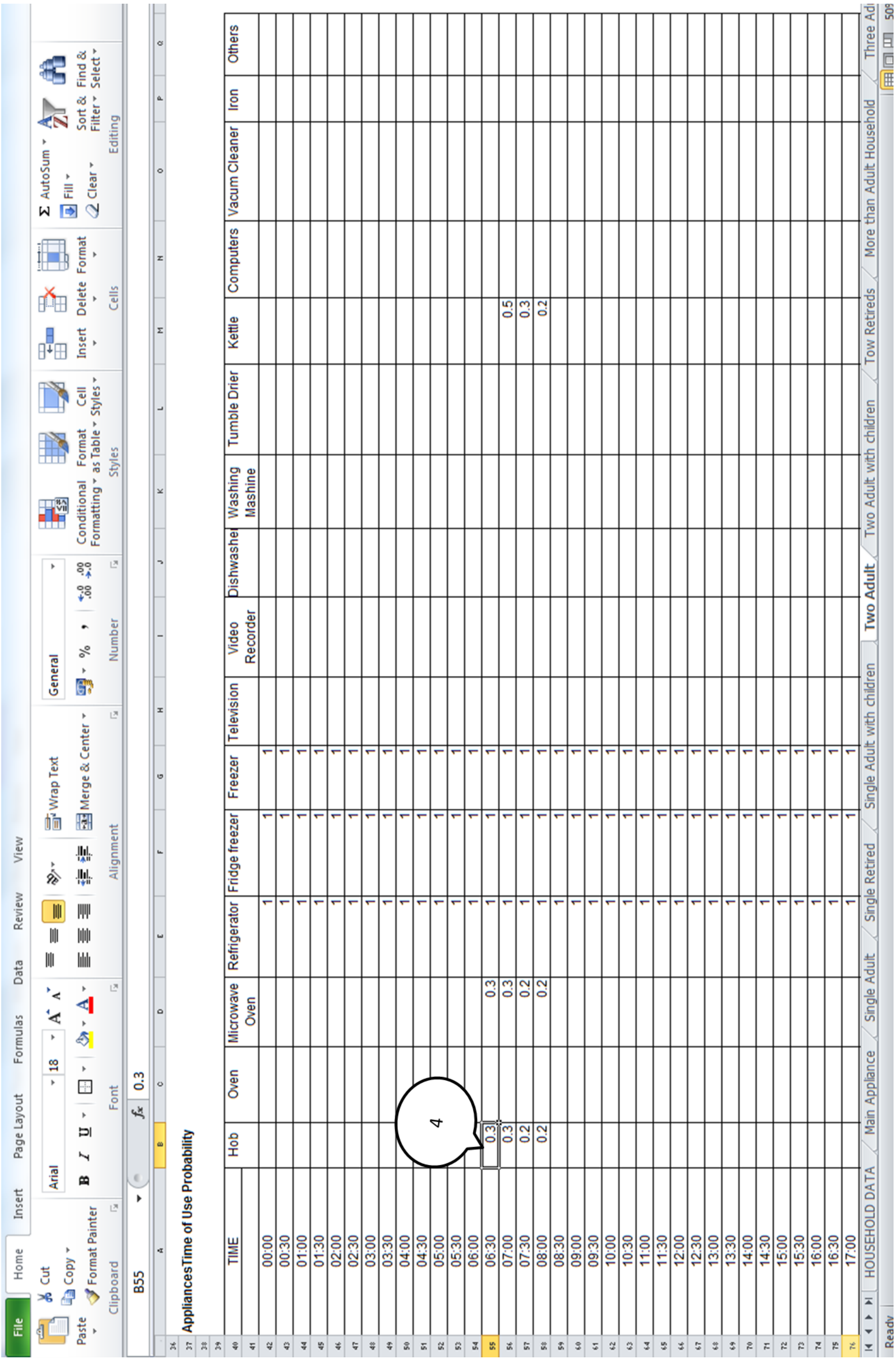

Figure C. 3 Appliances time of use probability

4. Calculate the probability of a household carrying out a particular activity during a 24 hour period based on questionnaire survey.

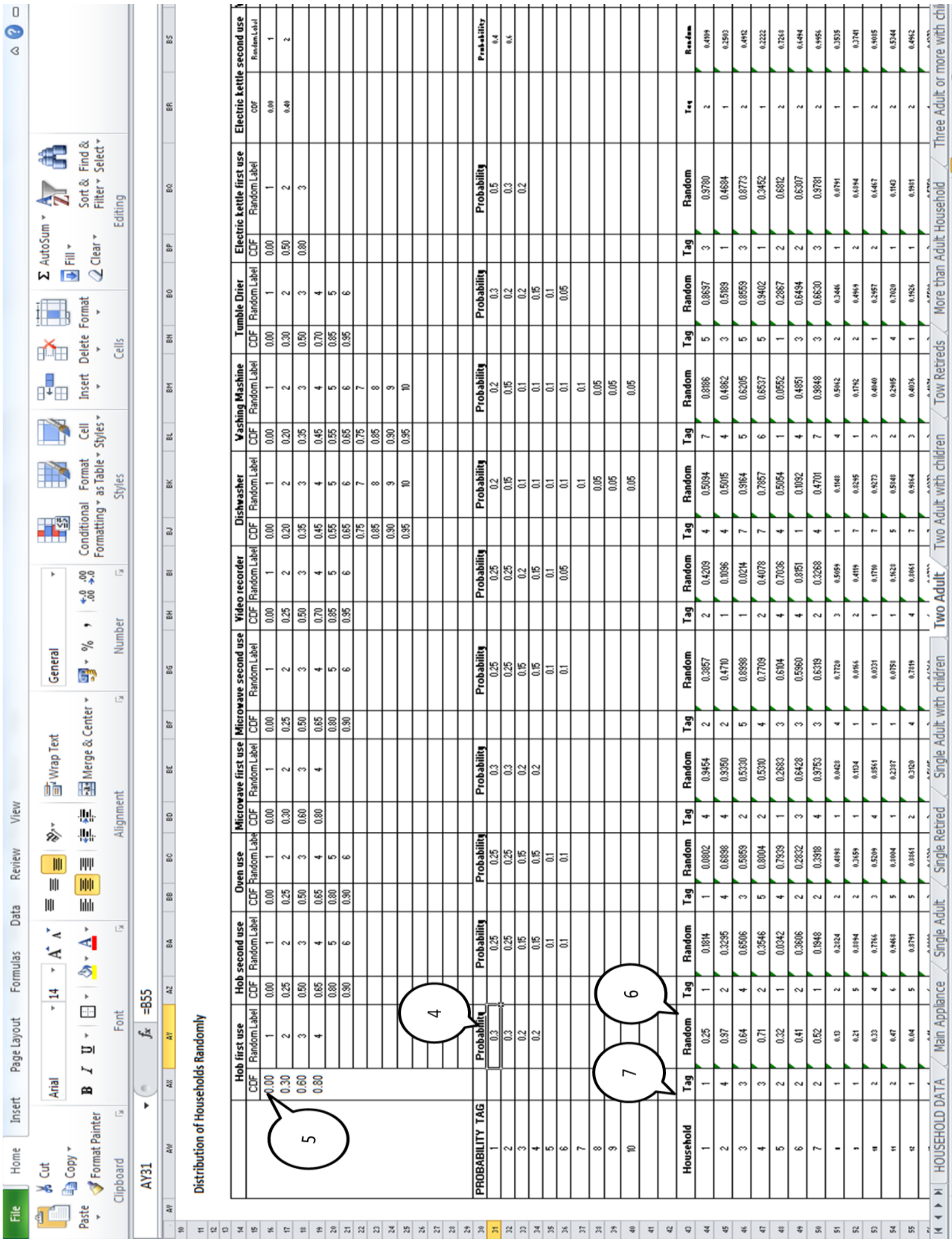

Figure C. 4 Random distribution of households

5. Calculate the cumulative distribution functions (CDF) (e.g. 0.30 =AX16+AY31).
6. Generate a random number (between 0 and 1) using RAND() function and then associate each value of RAND() function with possible value of cumulative distribution functions (CDF) for the whole households.
7. Use VLOOKUP function to find the tag of specific probability resulted from RAND function.

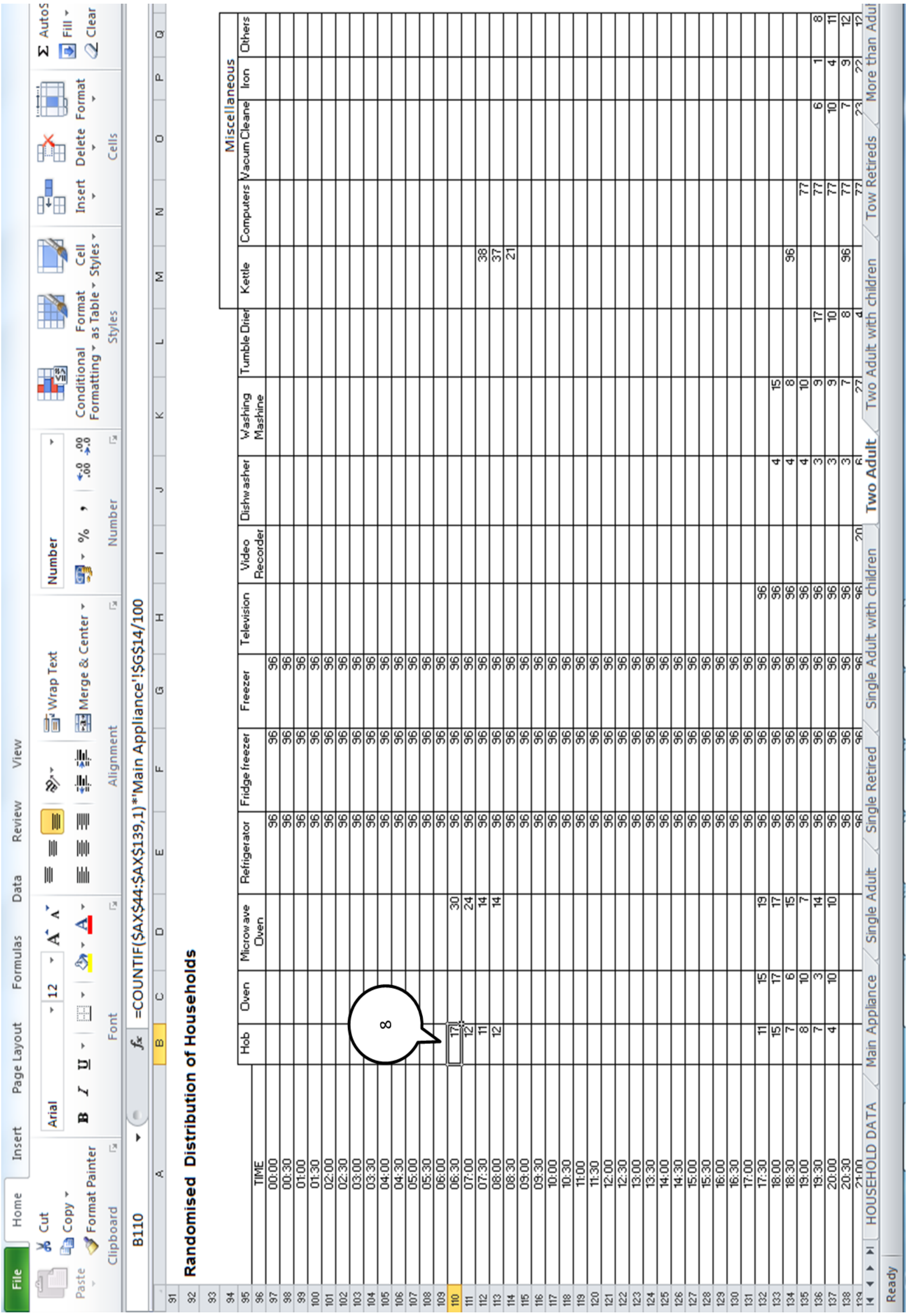

Figure C. 5 Distribution of appliances

8. Use COUNTIF function to count the No. of randomized distribution of Households appliances which meet the given criteria (based on ownership level) (e.g. 18 =COUNTIF($AX$44:$AX$139,1)*'Main Appliance'!$G$14/100).

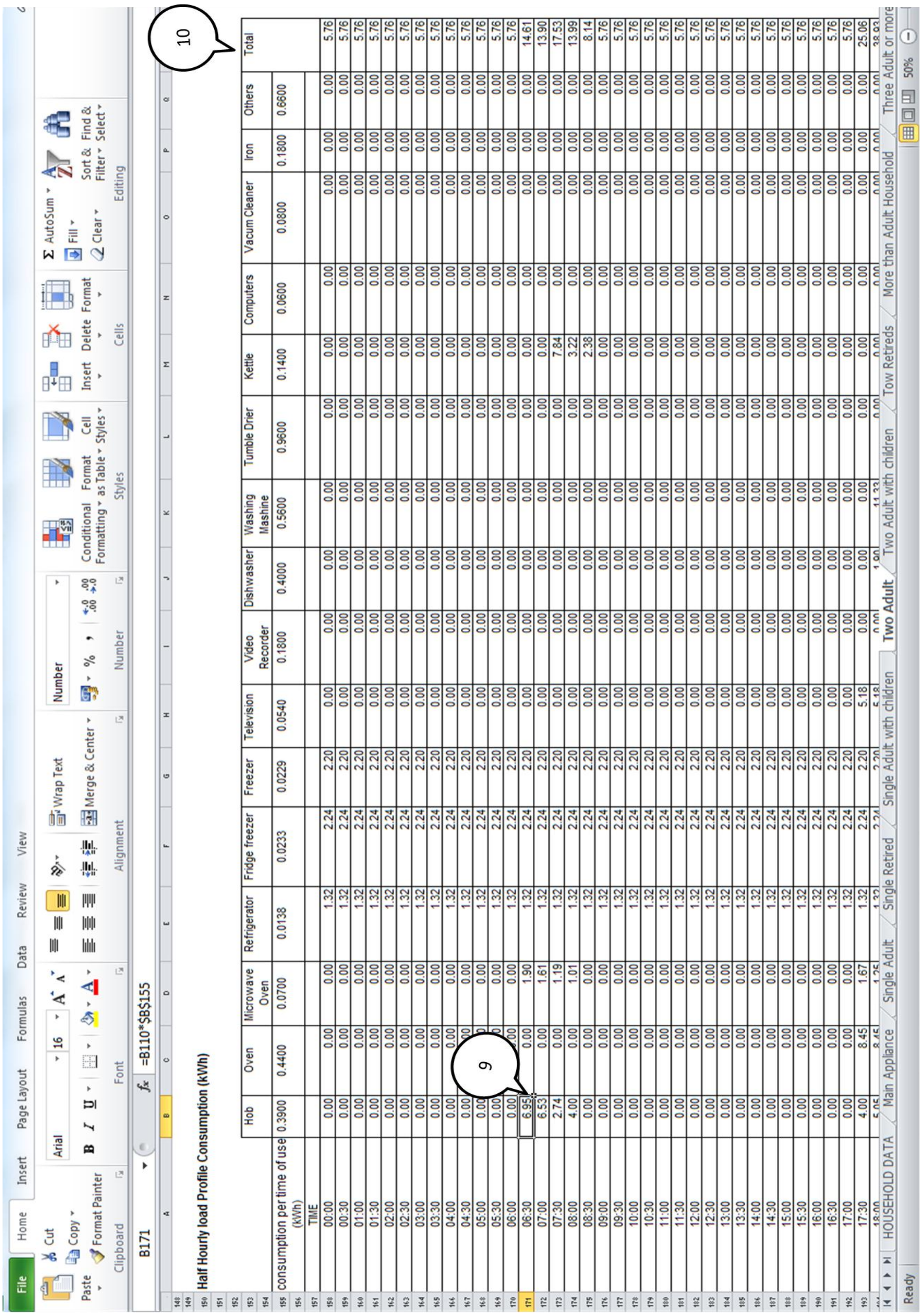

Figure C. 6 Calculations of half hourly load profile

9. Generate the half hourly load profile consumption for each appliance.
10. Aggregate the whole random profiles for all appliances to generate a daily consumption load profile for a known household.

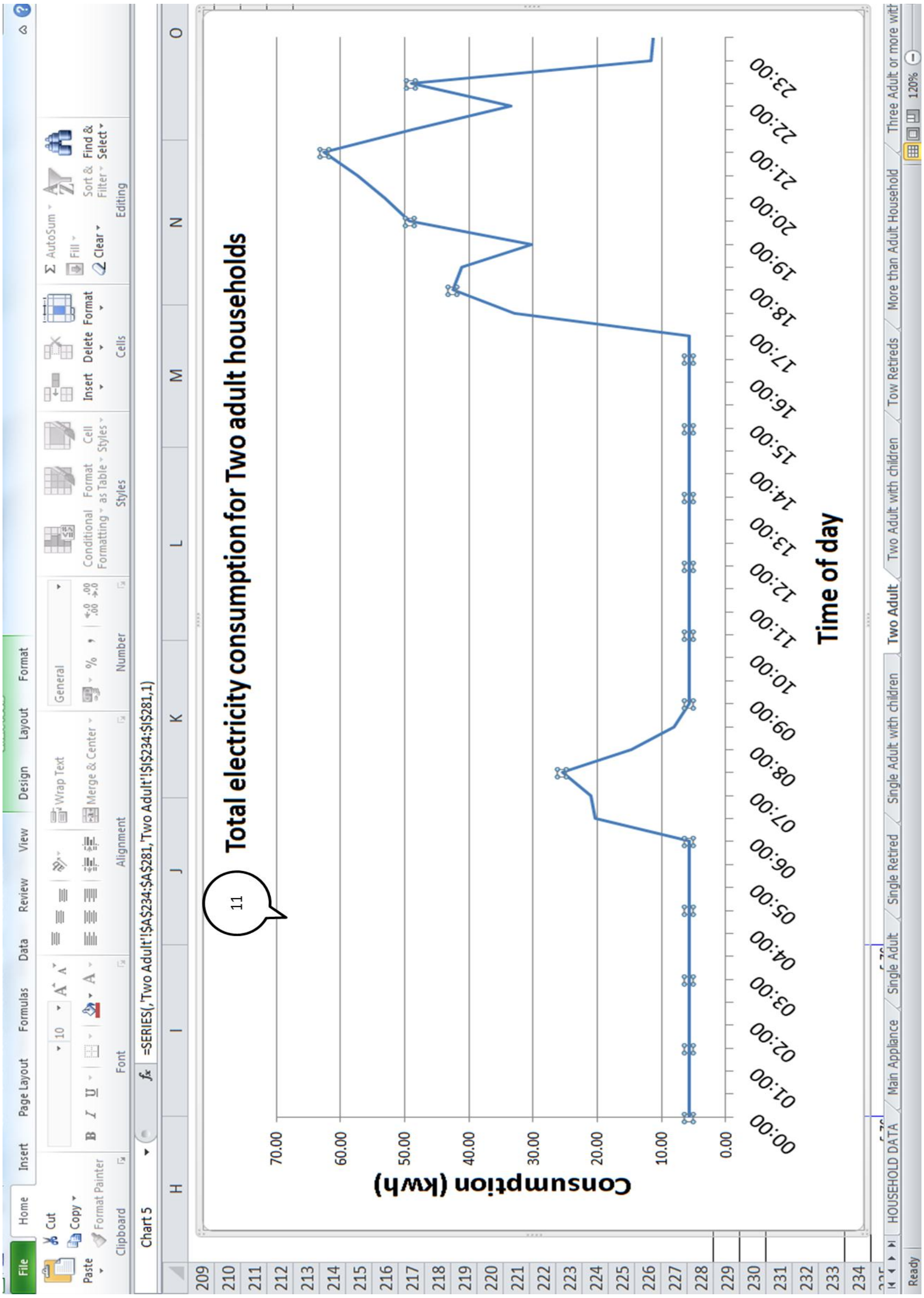

Figure C. 7 plots of the generated load profile

11. Plot the load profiles for each household type.