Demand response and embedded storage to facilitate diverse and renewable power generation portfolios in the UK

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Abstract

This thesis examines the growing problems surrounding the supply and demand of electric power in the UK, brought on by the structure of the power markets and the increasing move towards renewable generation as fossil based fuels become unavailable or unacceptable. The objective of the report is to propose a restructuring of the UK electric marketplace on the demand side, so that arbitrage returns. This will stabilise wholesale electricity prices, increase the reliability of the electrical network, and promote an attitude of efficiency and awareness in consumers.

A comprehensive software model has been produced. This is used to examine different scenarios of future energy use, renewable generation, real-time pricing and embedded electrical storage. The findings of this analysis are that demand response via real-time pricing is a more effective method of managing supply and demand than by attempting to provide additional amounts of generation capacity to cover winter demand peaks. The benefits occur not only in the capital expense required, but also in the resulting security of supply, average energy prices to the customer, and saleable load factor of existing plant capacity. It is also found that real-time pricing in conjunction with conservative estimates of demand elasticity provides a much better match between supply and demand than any implementation of embedded energy storage achievable at reasonable cost and technical complexity.

About the author

Andrew Roscoe received the B.A. degree in Electrical and Information Sciences Tripos at Pembroke college, Cambridge, England in 1991. He was awarded the M.A. degree in 1994, and elected to chartered membership of the IEE in 1996. Andrew worked for the GEC Marconi Research Centre in England from 1991 to 1994 and GEC Marconi Avionics in Edinburgh from 1994 to 1995. He was involved in antenna design and calibration, specialising in millimetre-wave systems and solid-state phased array radars. Andrew worked from 1995 to 2004 with Hewlett Packard and subsequently Agilent Technologies, in the field of microwave communication systems, specialising in test and measurement automation systems for personal mobile and satellite communications. During this time Andrew worked in Scotland, California and Washington state. Andrew was admitted to Strathclyde University in 2004, studying for the MSc in sustainability; Energy systems and the Environment. Andrew hopes to work in the UK Energy sector, in the field of active/responsive demand and network management.

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1 Introduction

This thesis examines the growing problems surrounding the supply and demand of electric power in the UK, brought on by the structure of the power markets and the increasing move towards renewable generation as fossil based fuels become unavailable or unacceptable. The objective of the report is to propose a restructuring of the UK electric marketplace on the demand side, so that arbitrage returns. This will stabilise wholesale electricity prices, increase the reliability of the electrical network, and promote an attitude of efficiency and awareness in consumers.

Reliable and sustainable energy supplies are crucial to the economic and social development of both present and future generations. Our agricultural, industrial, service, communication, leisure and domestic activities depend more than ever on a consistently available supply of energy. The structure of the electrical power market in the UK is not well suited to ensure this reliable supply, however. The wholesale price of electricity changes half-hourly, but the prices charged to consumers are largely independent of time, weather conditions, demand levels and available supply. Without any incentives to customers to modify their behaviour, the only reason that blackouts do not occur presently is that the vast majority of available generators are controllable to meet the expected demand, while the population as a whole is large enough to be fairly predictable in its behaviour.

Electricity can be stored but it is expensive and difficult at large scales. From a network perspective, the vast majority of electricity must be generated and consumed concurrently.

The supply and demand situation is changing, however. Record low average wholesale real prices of electricity purchased from the privately funded generators combined with regulation from Ofgem which limits sale prices to customers means that generators can be unwilling to continue business if return on investment is below average stock market returns. This effect has occurred in the UK in recent years, leading to generators being mothballed or cannibalised for spare parts. A mothballed generation plant can take many months to re-commission. A lack of on-demand generation lowers the margin between expected peak winter demand on cold snowy days and the total available supply. If demand exceeds available supply, there are very few measures that the UK transmission and distribution companies can take, and a blackout will likely occur.

Even more significantly, renewable generation is gradually providing a greater and greater share of our electricity. Much of the renewable power generation is weather dependent: wind speed, wave heights and sunshine will determine the amount of power available for generation at any instant in time. This means that, if renewables are to provide a significant proportion of our UK electricity, there are four options available to us, if we are to maintain a security of supply:-

1) A vast oversupply of renewable generation must be provided in the UK so that at the worst case weather conditions for both generation and demand, there is always enough power. Typically, the average achievable Load Factor[1] over a whole year for PV generation in the UK is 20% or less, and for wind turbines is about 30%, assuming that all power generated can be used. This implies that if wind and PV were major sources of energy, we would need at least a 3x overbuild of peak wind capacity and a 5x overbuild of peak PV capacity to meet any given peak power demand. When oversupply is provided, there will often be more energy than can be consumed, hence saleable load factors drop even further with dire financial consequences for the generators' revenue and consequently the viable energy price. The actual multiplication factors for overbuild might be larger, and will also depend upon cross-correlation of weather conditions between the portfolio of different generation types and the demand changes that tend to occur with those same weather conditions. It will also depend upon the geographical spread of the renewable deployment in relation to the size of the weather systems. Providing such a vast oversupply of generation will necessarily lead to much higher overall capital investment, energy costs and environmental impact.

2) Option two involves providing DC inter-connector links of very high capacity to Europe and beyond. This means that the variations in of supply and demand is spread much wider geographically, thereby reducing the statistical swings in available supply and demand by averaging them out over many countries and possibly also time-zones. This option also requires that the transmission grids within the UK and the other participating countries would need to be strong enough to provide or accept the huge sloshing of power around Europe. This scenario is both unlikely from a financial and technical standpoint, involving massive capital investment in the transmission networks. It also poses political and security-of-supply questions. The inter-connectors and the entire UK grid would be operating at a relatively low load factor and hence not used effectively from a financial investment perspective.

3) Option three imagines that we can realise some form of effective centralised bulk storage of electricity. If an amount of electricity equal to 10 or 20 days worth of UK consumption could be stored, then the renewable generation installed could be sized appropriately to our peak demands with only a relatively small overbuild factor. Very few cold and calm high-pressure weather systems would persist longer than 10-20 days during our peak demand winter months. However, current UK bulk storage in pumped hydro schemes is only equivalent to 30 minutes of our average electrical power consumption. It is unlikely that any further pumped storage facilities can be built as there are few suitable sites remaining the UK and those that are suitable will be subject to intense planning difficulties or excessive costs. Option three would only

[1] see appendix 7.1 for definition

be viable if some new technology becomes available for large-scale storage: centralised hydrogen stores or superconductivity might provide answers but are unproven at any required scale. The viability of such technologies is examined in Section 2.4.

4) Option four is that the demand for electricity can be manipulated to match the available supply in some way. This “**Demand Response**” is not a novel concept, but it is novel for electrical markets in the developed world. Every other competitive commodity market is influenced by the simple rules of supply and demand. When demand approaches or exceeds supply, prices rise. Consumers react by reducing their consumption; sellers make more money per unit sale of goods but sell less units. Some sellers who previously might not have sold goods may now decide to do so at a profit. When demand drops enough or the supply of goods rises, prices tend to drop and the situation reverses. In our electricity market, this cycle is interrupted by the structure of our electricity market and the regulator Ofgem. The prices that most electrical consumers pay is more or less fixed, no matter what the status of the supply or demand. If the cycle could be connected, by linking electricity prices to the supply vs. demand balance, then demand should modify itself by dropping when supplies are low and prices are high. This option is a technical, financial, and above all **social** solution. It involves us, the population, and the changing of our behaviour with respect to electrical energy. Our attitude to electricity consumption would forever more be linked on a daily basis to the weather systems and to the concurrent behaviour of our fellow consumers. This is a big change in our relationship with the on-off switch. We would be re-learning to value energy for the commodity it is, rather than a limitless resource. In the same way that we check the prices of petrol, houses and apples, we would be thinking about the current price of energy before buying it.

Any or all of these four options might be mixed in different proportions, indeed it is unlikely that any single one will provide a solution alone.

However, since options one to three are either technologically unfeasible or excessively expensive, this paper focuses on option four, demand response. It is shown that demand response can be an effective and economic method of matching supply to demand, and hence ensuring security of supply, for a high penetration of renewable power in the future. Demand response can also minimise the capital investment in the power grid to achieve the required supply quality and reliability. In the near term, demand response is the only method that can realistically be used to enhance the security of supply following unanticipated events such as a gas pipeline explosion, freak weather event or major problems at just one or two pivotal generator units.

A report by the New England demand response initiative (NEDRI, 2003 [23]) says the following about the role of short-term (i.e. day-to-day) demand response in New England's power markets :-

> *Growing experience with regional power markets in New England and across the nation has led to an almost universal understanding that an active demand response is crucial to both market efficiency and power system reliability. Demand response resources can contribute to efficiency and reliability in several different ways. One important opportunity is the role that short-term, price-responsive load can play in real-time and day-ahead power markets. The ultimate objective of efforts here is to create sufficient price-responsive load so as to improve the performance, efficiency and reliability of wholesale electricity markets. Several conceptual studies and actual experience in other regions (e.g., New York) have demonstrated that a relatively small amount of price-responsive load can enhance system reliability if there are reserve shortfalls and substantially reduce market-clearing prices during tight market conditions, producing significant benefits to consumers.*

1.1 Brief overview of contents

Chapter 2 describes the current supply and demand of electrical power in the UK. An estimate of the future electrical supply in the UK is also presented, along with a review of possible storage technologies. From this combination of knowledge and imagined future generation scenarios two questions are then posed: what will be the impacts on the allowable demand for electricity? What are the drivers for change on the demand side of the electrical market? Chapter 3 goes on to examine methods by which these changes might be brought about. Chapter 4 describes the structure and operation of a simulation tool which was developed during the course of this thesis. Chapter 5 describes detailed numerical analyses using this tool. Two possible scenarios representing near-term and future energy scenarios in the UK are examined. Chapter 6 presents overall conclusions, both from the simulations and this document as a whole.

More detailed objectives are stated in section 2.6, since the exact objectives are defined after the context of our energy challenges are described in chapter 2.

2 The supply and demand of electrical power

2.1 Where does our energy come from?

For many years the bulk of our energy has been sourced from fossil and nuclear sources which can be converted to energy of the required form with a high degree of controllability. Petrol and Diesel can be stored in relatively small tanks and used for transport. Coal, gas and oil of high calorific value per unit mass can be stored and burnt at will to produce heat, steam, motion or electricity. Fissile nuclear fuel can also be used to create electricity in a steady and predictable manner. These large thermal power plants can react to changes in electrical demand with advance notice in the timeframe of several minutes or hours, although gas turbine plants can react more quickly and some designs of nuclear plant only work efficiently at full load. Other traditional bulk power generation in the UK includes hydro-electric generation which can be controllable at will in a matter of seconds subject to plant operating conditions and the catchment's rainfall available each season.

Our modern society has become used to a supply of energy that is available in a "just-in-time" basis. We do not store our own supplies of coal, logs or gas for our domestic or industrial needs. We assume that gas will flow to our heating boilers and cookers when we turn the tap; we take for granted that our lights and TV sets will stay on 24 hours a day without interruption. More than that; we assume that these things will occur all year round irrespective of weather conditions or other unforeseen events. Indeed, the gas and electric regulators will financially punish any energy supply utility that does NOT fulfil these expectations. The pressure on the energy supply companies to deliver a reliable service has never been greater.

At the same time, climate change arguments are driving us to shift our energy portfolio away from fossil fuel sources. More importantly, they are running out – at least from a UK political standpoint. The amount of economically recoverable global oil and gas reserves depend upon energy prices and technology advances, but are unlikely to surpass 50-100 years each unless consumption reduces substantially – and the trend is currently towards increasing annual consumption. The reserves of these are mainly in countries and locations which do not possess a historical political record of stability that we should rely on for our dominant energy supplies; from 2005 onwards the UK will be a net importer of gas, initially mainly from Norway but within a few years most of our gas will be pipelined from Siberia. UK oil reserves are virtually depleted unless the controversial "Atlantic Frontier" reserves are tapped. There are substantial world coal reserves, at around 200 years, and the UK has its own substantial supply which could be recovered, although there are substantial local environmental and health impacts of doing so. Currently, most of the coal for UK electricity generation comes from Poland and China. Despite the fact that the coal is of inferior standard to UK reserves, due to labour costs our coal is deemed economically unviable and will remain underground unless foreign reserves become unavailable or much more expensive.

Nuclear fission power will only be sustainable if the fast breeder and/or reprocessing programmes are reinstated so that both the naturally fissile ^{235}U and the "inert" ^{238}U (99.3% of the mined uranium) can be utilised to create energy, via the Plutonium intermediate product. In this case, at current rates of usage, the land-based ore stocks would last many thousands of years. However, reprocessing plant operational difficulties and emissions, combined with the political difficulties of dealing with and transporting the Plutonium has led to all commercial fast breeder programmes worldwide being suspended indefinitely. While global nuclear power centres on traditional fission techniques which only use the fissile ^{235}U, land-based ore stocks will be depleted in 300 years at current rates of usage (NIA, 2000 [28]), much less if Asia, Europe and the US increases their rate of usage. The UK has insignificant reserves of Uranium.

Nuclear fusion might be realised on an industrial scale, or nuclear fast breeders might become politically acceptable; both are real possibilities but outside the scope of this report, But in the absence of these solutions to our energy problem, a steady transition to renewable "clean" energy is the best option available to satisfy our long-term demand for reliable energy in the UK.

Renewable energy can be harnessed from many sources, but as a generalisation these sources are less concentrated than fossil fuel based sources and are subsequently harder to gather into high grade energy like electricity, high-temperature heat or a high-calorie combustible chemical fuel. To provide a substantial proportion of total UK power from renewables requires a portfolio of energy sources rather than a mass investment in a single technology.

Current total UK energy use, in 2002, was approximately (DTI, Energy Trends 2003 [11]) :-

	TWh of raw fuel	Percentage of UK fuel use
Petrol, DERV	418.68	18.5%
Aviation Fuel	139.56	6.2%
Electricity, domestic	336.63	14.9%
Gas, domestic	410.94	18.2%
Electricity, industrial	635.28	28.1%
Gas, industrial	316.17	14.0%
	2257.26	100%

Table 2-1 Current total UK energy use, RAW fuel

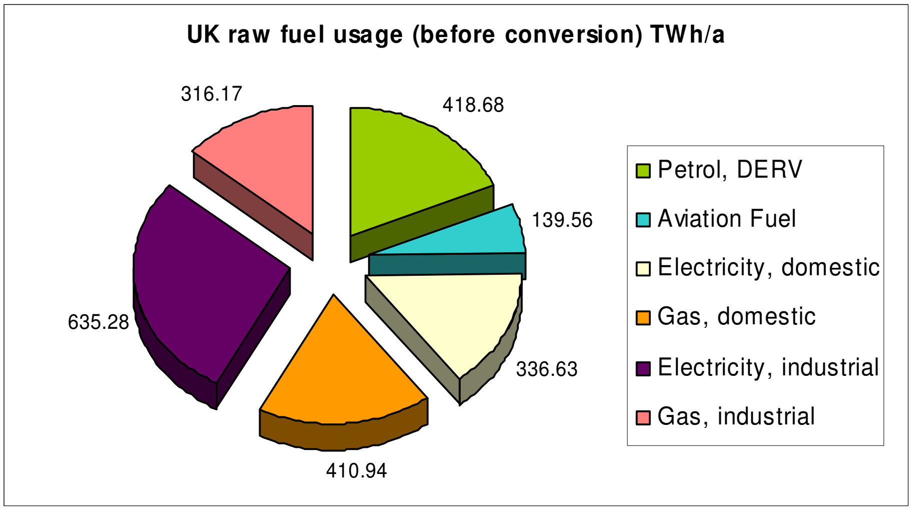


Figure 2-1 Current total UK energy use, RAW fuel

The DTI have published an energy flowchart which shows graphically how raw fuels are used, converted and consumed in the UK. It is available from [9].

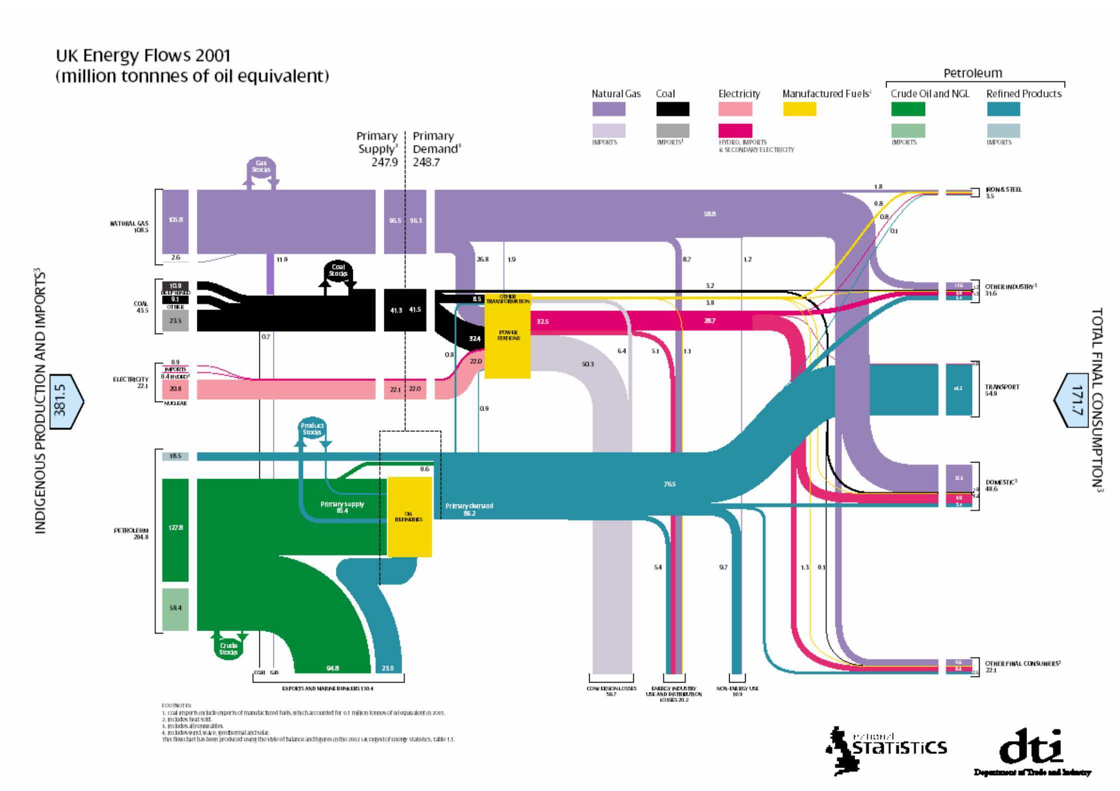


Figure 2-2 Current total UK energy use flowchart

Of the electrical power we use, the energy is sourced from the following sources [11].

	Raw Fuel Use TWh / a	Percentage of UK raw fuel use
Coal	**344.25**	**15.3%**
Oil	**15.00**	**0.7%**
Gas	**326.34**	**14.5%**
Nuclear	**236.32**	**10.5%**
Hydro	**4.77**	**0.2%**
Other renewables	**24.07**	**1.1%**
Other fuels	**12.68**	**0.6%**
Imports	**8.49**	**0.4%**
	971.91	**43%**

Table 2-2 Current RAW fuel use to create UK electricity

The actual amount of electrical power that we currently use is significantly less than the 970TWh/a figure, as the raw fuels are not converted to electricity at 100% efficiency.

The actual electrical generation mix capacity and output figures for the UK in 2002 were [11] :-

Electrical Generation CAPACITY (maximum) in GW			Actual Supplied	
	Total (GW)	Total potential (TWh/a)	TWh/a	Load factor
Coal/Steam	22.5	196.7	118.59	60%
Oil/Steam	2.7	23.7	4.24	18%
Mixed/Steam	10.0	87.6	3.56	4%
CCGT	22.1	193.5	148.74	77%
Nuclear	12.5	109.4	81.09	74%
Gas/Oil Engine	1.5	12.8		0%
Hydro (generating)	1.5	12.8	3.86	30%
Hydro (pumped storage)	2.8	24.4		0%
Other renewables	1.1	9.9	6.24	63%
Imports	2.0	17.5	8.41	48%
	76.6	**688.4**	**374.7**	**54%**

Table 2-3 UK electrical generation mix capacity and output

Our actual peak UK demand is approximately 62GW against a capacity of 76.6GW giving a theoretical reserve capacity of approximately 20% in hand during winter peak load, assuming all generation is operationally available. In practice the margin is much smaller, as a proportion of generators will always be unavailable either for operational or resource-limited reasons. Also, transmission and distribution systems will impose their own constraints on the power transfer. Oversupply of peak capacity is also inefficient from a capital investment point of view. In reality the margin between peak winter demand and available supply capacity is much smaller than 20%, maybe 5% to 10%.

We can also deduce from the tables above that the aggregate efficiency of generation is approximately 374.7/971.91 ~= 36% which is a figure dominated by the efficiency of the coal, gas and nuclear plants.

2.2 Where will our energy come from?

Calculations and references in appendix 7.2 detail approximations of UK future potential renewable energy sources. They can be summed up as follows :-

	Estimate of UK peak electricity capacity potential	Load factor	Controllable ?	Annual energy estimate (Peak capacity * 8.76 [TWh/a/GW] * LF)
Hydro	1.5 GW	30%	Yes	3.9 TWh
Domestic PV	30 GW	<20%	No	52 TWh
Solar water	(60 GW displacement)	<20%	No	(105 TWh)
Land-based wind	40 GW	30%	No	105 TWh
Offshore wind	40 GW	40%	No	140 TWh
Wave	20 GW	40%	No	70 TWh
Tidal	100 MW	50%	Predictable	0.5 TWh
Domestic organic waste	200 MW	High	Yes	1 TWh
Wood	10 GW	High	Yes	90 TWh
Biodiesel (10% of UK landmass!)	7% of current transport needs		Yes	
Total electric contribution	~142 GW (~200GW including displacement)	20-40%	Predominantly No	~462 TWh (~570 TWh inc displacement)

Table 2-4 UK potential renewable electrical generation mix capacity and output

Clearly, these sources combined, as calculated above, could in theory supply enough electrical energy to satisfy our current electrical demand of 375 TWh/a as shown in Table 2-3. However, the electricity might not be available when demand would ideally call for it. Without demand response or vast storage activities, it is unlikely we will be able to match supply with demand. Only a vast overbuild of domestic PV or bulk wind power, relative to even the optimistic figures above, will be able to release more renewable energy.

In future years, we can imagine a situation where there might be no fossil-based oil, coal or gas available. This report will focus upon the domestic, commercial and industrial energy requirements which will need to be met. Analyses will be carried out, firstly assuming roughly current rates of electrical energy consumption (i.e. gas is still available) but an increased percentage of renewables in the electric generation portfolio. Secondly, the analysis will be extended to imagine the case where our current natural gas energy requirements need to be met by an entirely electrical power supply. Since current UK electrical power consumption is about

370TWh/a and gas consumption is about 730TWh/a, displacing our entire gas use by electricity means a factor of 3 multiplication in required electricity supply. This would be a substantial adjustment to the UK power system.

In this report, transport energy requirements from non-fossil sources will not be considered in the detailed analyses. Biodiesel production could account for a small (7%) proportion of our current requirements, assuming we devoted a massive (and unrealistic) 10% of the entire UK landmass to intensive production. More realistically, future transport without fossil fuels will be based upon hydrogen, battery or superconducting storage technologies. All these require energy to be generated, primarily via electricity, and these will add another 400TWh/a to our UK electrical requirements. The time of conversion from electricity to the stored medium might be controllable and might provide an interesting line of work for future demand-response study, particularly since the amount of energy required is large. Until transport technology roadmaps become clearer, and the hydrogen economy truly evolves (or not), detailed study is difficult and will not be attempted here.

2.3 The current electricity market situation in the UK

In the UK, similarly to many developed countries, the electricity market has been deregulated and the services “unbundled”. Historically, the CEGB was responsible for generating and transmitting the power, while nationalised regional utilities were responsible for distributing the power to homes and businesses, and providing the “service” face of the power industry. Now, the market is privatised and split into many individual businesses. Generators can be fully independent private enterprises, while some of the largest pivotal generators can be regulated private companies.

The transmission grid is run in England and Wales by Transco; it makes profits from the quantities of power that it transmits at 275kV and 400kV (HV), and attempts to link transmission charges to the area of generation and demand. These transmission charging fees are paid by generators and RECs (Regional Electricity Companies) and are known as TNUoS (Transmission Network Use of System) and BSUoS (Balanced Services Use of System). These charges are based upon location, as they are evaluated by measurement of the peak demand at the Grid Supply Points (GSP) [19] and Bulk Supply Points (BSP). Generators attached to an area of oversupply have to pay higher fees to transmit their power via the grid, since the power will be used further away and cause more loading of the network infrastructure. Generators attached to an area of undersupply might have to pay lower (or even negative) fees to transmit their power, since their generated power eases the burden on the network. This charging system correctly encourages bulk generation in areas of undersupply, but poses economic problems for larger renewable generation schemes in remote areas where resources are high but demand is low. The current charging system also rewards transmission operators for the sheer amount of power that they transport; they take no part in the actual purchase or sale of the electricity which flows in their conductors, hence, without regulatory controls they have no financial interest in the market price or efficiency.

The distribution system in the UK generally refers to the demand-side power network at voltages of 132kV and below (some HV, mostly MV and LV) although the upper voltage level boundary between transmission and distribution varies according to location and demographics. The distribution networks are split into several different DNOs (Distribution Network Operators) who are responsible for the physical infrastructure of the MV and LV networks. Historically the distribution networks were responsible for simply distributing power from the transmission network to the customers. However, as embedded generation becomes more popular, the role of the distribution grid is changing. Generators attached to the distribution grids, many exploiting small renewable energy resources, can both reduce strain on the network but also add to it. The networks were designed for a one-way predictable flow but now it is possible to flow in either or many directions. This has many effects, of which voltage rise and complications to network protection schemes are two of the largest.

Use of the nework is funded by DUoS (Distributed Use of System) charges paid by the REC customers to the DNO, based upon a Distribution Reinforcement Model (DRM). This model attempts to estimate the capital cost required to increase the distribution demand capacity by 500MW, and then spreads the cost between demand customers on per-KVA and per-KWh bases. For generators attached to the distribution networks, no DUoS is charged but instead a connection charge is levied. Until recently this was a deep charge, reflecting the generation connection cost plus any network upgrades at the same or the next highest voltage level to accommodate the extra power. Recently the charging has changed to a shallow charge, reflecting only the connection equipment for the actual new generation; network upgrades further upstream are financed by all users via DUoS. In future, a fairer arrangement might be to waive even the shallow connection charge for embedded generators and include them in the DUoS fees.

These DNOs are also the default “service providers” by name in each physical region, although the service provider will set up a separate financial entity as an REC to do this business. The REC takes payment from customers in exchange for electrical connection, power use and customer service. In each region, however, since, deregulation, rival competitive service providers (RECs) may provide the same physical service but at differently competing financial payment terms and pricing structure packages. The RECs buy and sell power from NETA, sell power to customers, and pay the DNOs and national grid operator their DUoS and TNuOS charges respectively.

This competition and complex arrangement has been termed “unbundling” since the generation, transmission, distribution and customer service/billing parts of the power industry have now been unbundled from one nationalised entity into many separate parts to encourage competition and innovation in the industry. Only in Scotland do the transmission and distribution bundles remain, in the Scottish Power and Scottish and Southern areas, and this will shortly change with the introduction of the BETTA arrangements which will supersede the NETA arrangements.

All this is well and good, and encourages extremely cheap energy for customers. Indeed, The regulator Ofgem uses an RPI-X control to regulate the price that the RECs are allowed to sell electricity to us, the customers [19]. RPI-X means that the sale price of electricity may only rise each year by the retail price index (RPI) minus a figure of X%, which is the efficiency gain which Ofgem expects the transmission and distribution network operators to achieve in each given year.

The downside of the Ofgem controls is that we are exposed to the same potential situation as faced California in 2000. The RECs and service providers are forbidden to charge any more than a fixed (competitive) rate for electricity. This means they have no means of reducing demand by using price as a control, even on a seasonal basis. Their revenue (and the revenue of the transmission companies) is linked to the volume of power that they deliver; hence neither the DNOs, REC service providers nor transmission companies have any revenue-based incentive to encourage energy efficiency or energy use reduction – quite the reverse; they would like to sell more electricity. At the same time, revenues available to the REC service providers are limited by the price controls. This places an upper limit on the amount that generators may be paid. If generation costs rise due to the increased costs of renewable rollout or increased fossil fuel costs, there is no way to pass this to the customer unless Ofgem changes the allowed charging rates, and this happens possibly once a year. If generators are not paid enough to operate, then as private companies they may simply declare bankruptcy and cease operations. Very quickly, supply can fall below demand and blackouts are a certainty. This was the situation in California and it could happen in the UK.

2.3.1 Introducing market elasticity and the inelastic UK power market

At this point, the economic terminology of market elasticity should be explained.

If a product X sells a quantity Q_{X1} at price P_{X1}, and a quantity Q_{X2} at an increased price P_{X2}, then the own-price elasticity is expressed as:-

E = % change in demand for X divided by % change in price of X

$$E = \frac{\left(\frac{\Delta Q_X}{\overline{Q}_X}\right)}{\left(\frac{\Delta P_X}{\overline{P}_X}\right)} = \frac{\left(\frac{Q_{X2} - Q_{X1}}{\frac{1}{2}(Q_{X1} + Q_{X2})}\right)}{\left(\frac{P_{X2} - P_{X1}}{\frac{1}{2}(P_{X1} + P_{X2})}\right)}$$

Equation 1 Own-price elasticity of demand

So if demand drops from 1 to 0.8 when price increases from 1 to 1.2, $E = \frac{\left(\frac{0.8-1}{0.9}\right)}{\left(\frac{1.2-1}{1.1}\right)} = -1.22$

Equation 1 may be inverted to find the new demand level as a function of price.

$$Q_{X2} = Q_{X1}\frac{(1+a)}{(1-a)} \text{ or } Q_{X2} - Q_{X1} = Q_{X1}\frac{2a}{(1-a)} \text{ where } a = E\frac{(P_{X2} - P_{X1})}{(P_{X2} + P_{X1})}$$

Equation 2 Demand as a function of own-price elasticity

Generally, elasticities for commodities are negative, i.e. the more something costs, the less demand there will be. Strongly negative elasticities (E<-1) suggest that customers are unwilling to spend more in order to acquire the product if the price rises, but they will buy a lot more if the price drops. Revenue therefore increases as the price drops when E is highly elastic. Weakly negative elasticities (-1<E<0) suggest that customers are willing to pay more as the product is desirable enough to warrant the extra expense. Revenue will drop as price lowers, since demand is not increased enough to cover the revenue losses from reduced demand. Positive elasticities imply that customers will buy more of something if it costs more. This is counter-intuitive but occasionally occurs when the desirability of an object is enhanced by the perceived value due to cunning marketing campaigns[2].

The table below gives an indication of customer behaviour for some examples of elasticity.

Reference price	**75**	**£/MWh**						
Actual prices	**Elasticity (+0.1 to -1.5) and resulting relative demands**								
£/MWh	-1.5	-1.25	-1	-0.75	-0.5	-0.25	-0.1	0	0.1
25	7.00	4.33	3.00	2.20	1.67	1.29	1.11	1.00	0.90
50	1.86	1.67	1.50	1.35	1.22	1.11	1.04	1.00	0.96
75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
100	0.65	0.70	0.75	0.81	0.87	0.93	0.97	1.00	1.03
125	0.45	0.52	0.60	0.68	0.78	0.88	0.95	1.00	1.05
150	0.33	0.41	0.50	0.60	0.71	0.85	0.94	1.00	1.07
175	0.25	0.33	0.43	0.54	0.67	0.82	0.92	1.00	1.08
200	0.19	0.28	0.38	0.49	0.63	0.80	0.91	1.00	1.10
225	0.14	0.23	0.33	0.45	0.60	0.78	0.90	1.00	1.11
250	0.11	0.20	0.30	0.42	0.58	0.76	0.90	1.00	1.11
275	0.08	0.17	0.27	0.40	0.56	0.75	0.89	1.00	1.12
300	0.05	0.14	0.25	0.38	0.54	0.74	0.89	1.00	1.13
325	0.03	0.12	0.23	0.36	0.52	0.73	0.88	1.00	1.13
350	0.01	0.11	0.21	0.35	0.51	0.72	0.88	1.00	1.14
375	0.00	0.09	0.20	0.33	0.50	0.71	0.88	1.00	1.14
400	-0.01	0.08	0.19	0.32	0.49	0.71	0.87	1.00	1.15
425	-0.02	0.07	0.18	0.31	0.48	0.70	0.87	1.00	1.15
450	-0.03	0.06	0.17	0.30	0.47	0.70	0.87	1.00	1.15
475	-0.04	0.05	0.16	0.29	0.47	0.69	0.86	1.00	1.16
500	-0.05	0.04	0.15	0.29	0.46	0.69	0.86	1.00	1.16

Table 2-5 Example demands for electricity based upon different elasticities and prices

[2] A classic example is the Parker 25 fountain pen, whose sales were poor as it was perceived as too cheap and tacky, until the price was increased and sales rocketed. Also, the beer Stella will always be "reassuringly expensive".

It is worth noting that elasticities are neither necessarily linear nor constant. As market prices increase or decrease with time, the elasticity of a certain product might change if the price is extremely cheap or expensive. Elasticities might also change with time dependent upon the perceived value of the product due to market or social effects.

The cross-price elasticity of demand describes how demand for a good X varies with the price of good Y. For example, off-peak electricity sales will be higher if on-peak electricity prices are higher. Cross-price elasticities are therefore expected to be positive, defined by:-

E = % change in demand for X divided by the % change in price of Y

$$E = \frac{\left(\frac{\Delta Q_X}{\overline{Q}_X}\right)}{\left(\frac{\Delta P_Y}{\overline{P}_Y}\right)} = \frac{\left(\frac{Q_{X2} - Q_{X1}}{\frac{1}{2}(Q_{X1} + Q_{X2})}\right)}{\left(\frac{P_{Y2} - P_{Y1}}{\frac{1}{2}(P_{Y1} + P_{Y2})}\right)}$$

Equation 3 Cross-price elasticity of demand

An additional less common elasticity definition, called the elasticity of substitution, is sometimes used within the power industry. Elasticity of substitution refers to two goods X and Y that are essentially the same good (direct substitutes), bought at different times.

$$E = -\frac{\Delta\left(\frac{Q_X}{Q_Y}\right)}{\Delta\left(\frac{P_X}{P_Y}\right)} = -\frac{\left(\frac{Q_{X2}}{Q_{Y2}} - \frac{Q_{X1}}{Q_{Y1}}\right)}{\left(\frac{P_{X2}}{P_{Y2}} - \frac{P_{X1}}{P_{Y1}}\right)}$$

E = - % change in ratio of demand for X:Y divided by the % change in ratio of prices X:Y

Equation 4 Elasticity of substitution

Electrical power demand in the UK is perfectly inelastic in a real-time basis. UK Electrical prices charged to domestic customers can in no way react to changing supply and demand characteristics on timescales less than about a year, when Ofgem allows price increases. The only elasticities in the day-to-day domestic UK electricity market are the “economy-7” and “white-meter” schemes which encourage night-time use of off-peak electricity. These are useful schemes and have fulfilled a requirement to partially flatten the daily load profile for many years, but they are not flexible enough to provide the security of supply and network reliability that we demand, while still allowing a more time-varying and unpredictable generation profile that renewables imply.

2.3.2 Price volatility and load curves

Behind the scenes, electrical power is not traded at these regulated prices; it is a free market. In England and Wales, power trades occur under the NETA agreements, which are shortly to be superseded by the similar BETTA arrangements and will also include Scotland. Every half hour, NETA purchases blocks of power from the generators and sells it to RECs via a system of bidding and offering, known as the "Balancing Mechanism" [27]. The market price is the highest trading price at any instant. Crucially, the supply and demand market reigns free in the balanced mechanism of power trading. It is only the final end users – us, that do not appreciate it. On days and at times when available generation capacity exceeds demand, the wholesale electricity prices settle to low levels approximating the actual true cost of generating the power competitively from the cheapest major generation technology (probably bulk coal), which is currently about £15-20/MWh. In some cases, generators may in fact agree to sell power at a loss, as some revenue is better than no revenue, and the sale can be a loss-leader to remain in the market and exploit higher energy prices to come. Indeed, on days and at times when energy demand rises to within striking distance of the maximum available supply, the energy price begins to rise and does so in a very sharp manner. The rise of the energy price vs. the available in-hand power does not rise in a normal fashion as in other commodity markets. Demand for electricity changes very little as demand approaches the limits of supply; we as consumers have little idea when these times and days are, so how are we supposed to conserve power at the appropriate times and stabilise the market?

Generators that can exploit these higher prices will be at a competitive advantage, and larger generators can exploit the market more than small generators. Lafferty et al [22] describe various definitions of "pivotal" power sellers. These definitions are essentially identical but come under the acronyms of SMA (Supply Margin Assessment) and RSI (Residual Supply Index). RSI is used in California and can be determined for each generator every half hour by dividing the overall power demand by the overall available power from all available generators except generator X. If RSI_X is less than 1, then the generator (seller) is pivotal and any bid made by X must be accepted to avoid a blackout. SMA is a similar test but determined on a peak-demand-per-day basis. If a seller is pivotal at a particular time or half-hourly bidding period, it may bid any sum of money for the power generated and the bid must be accepted or blackouts are inevitable. The market for the power demand is perfectly inelastic as we have seen, so there is no sales volume penalty for a pivotal seller raising the market price to almost limitless amounts in cases of shortage. This is why the market price of power rises so sharply as demand approaches the supply limit.

2.3.2.1 Demand forecasting in the UK

Figure 2-3 shows the "load duration" curve for England & Wales in 2001. This curve is representative of most power networks in developed countries. It shows that demand only approaches the top 10% of peak supply capacity for less than 5% of the time.

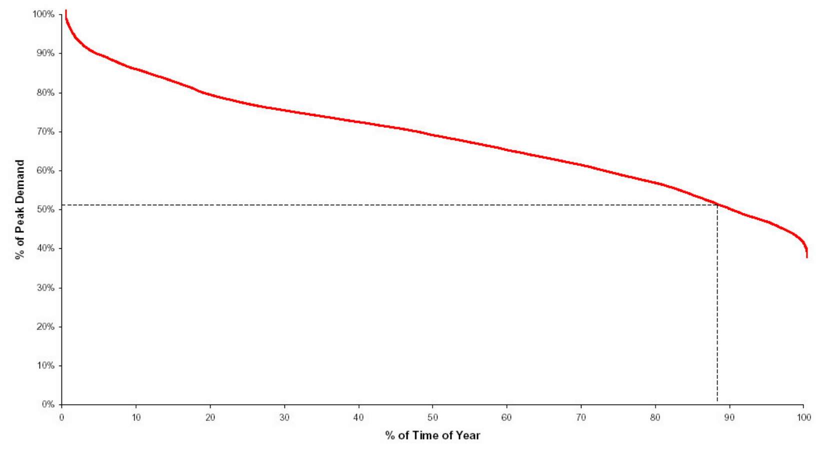


Figure 2-3 Load-duration curve for England & Wales, 2001 [25]

To balance the supply and demand of electricity in England and Wales, the Balancing Mechanism organisation receives forecasts for demand from various sources and distribution companies (the DNOs). There are a number of different forecasts for the day-day operation of the network, and these are continually updated as each day progresses.

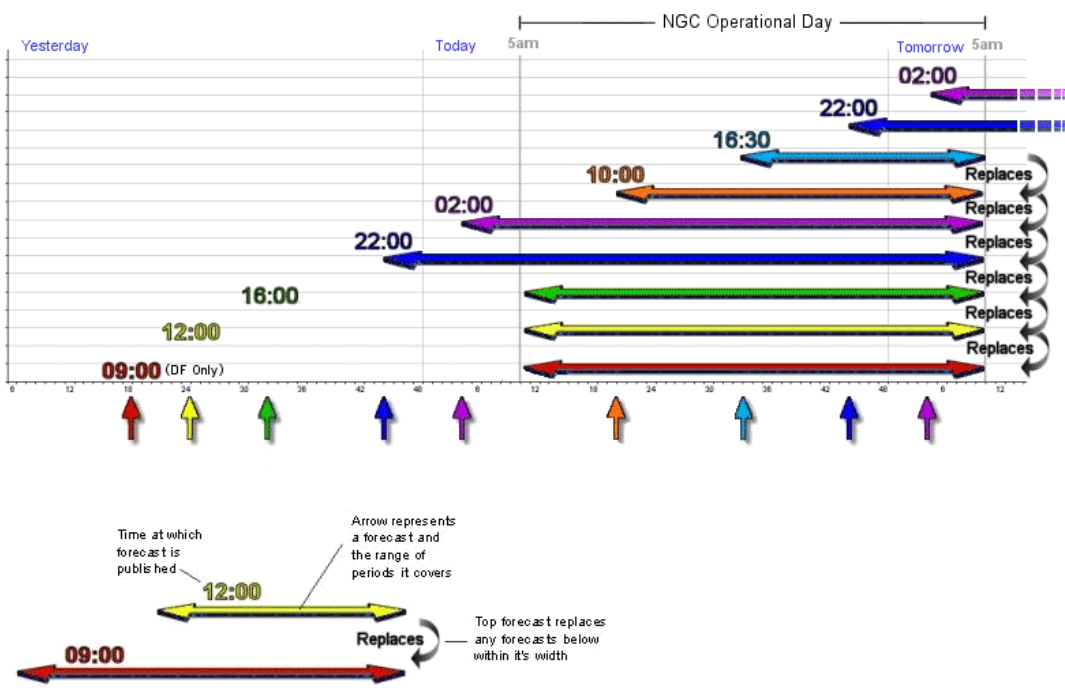


Figure 2-4 Forecasting schedule within NETA

The bulk of the required power can be purchased ahead for a given day, based upon the reasonably accurate demand forecast which is available. This is based upon the previous day's demand, the weather forecast, the day of the week, known TV schedules and major sporting or media events. As a day progresses, the actual weather and random events mean that the demand deviates from forecast. Power is traded with generators and RECs to balance the difference. In addition, the forecast for the remainder of the day is modified so that last-minute trading is reduced as far as possible. These last-minute power trades are the most volatile in terms of pricing.

As well as short-term forecasts, long-term forecasts are published.
The next three diagrams show the forecast demand and capacity for England and Wales for weeks 28-53 of 2004 and weeks 1-24 of 2005.

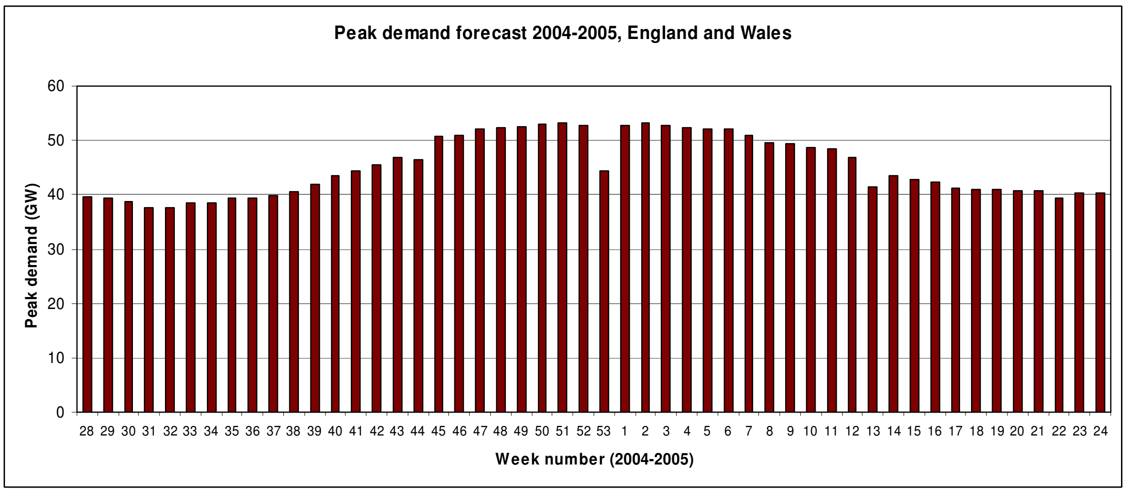


Figure 2-5 Demand forecast 2004-2005, England & Wales

Demand increases in winter, although there is a marked reduction in demand over the Christmas week, due to shutdowns at industrial plants, and a smaller drop at Easter. The minimum demand occurs at week 31 to 32, in August.

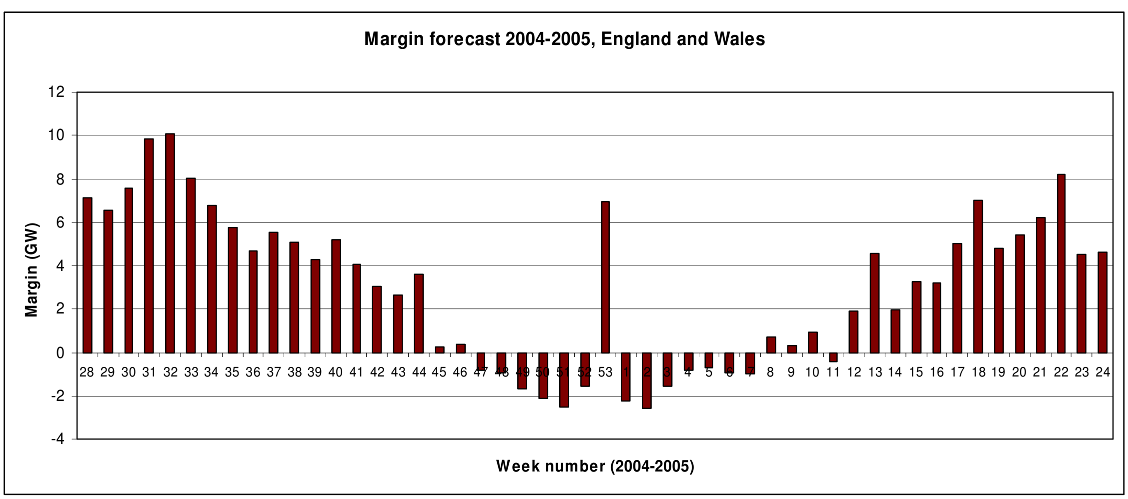


Figure 2-6 Margin forecast 2004-2005, England & Wales

The margin of supply over demand changes as expected. The Christmas drop in demand forms a marked feature in the data. Summer margin is not normally a problem, although day-to-day changes and unexpected outages of generation plant can still cause short-term energy shortages. During winter, there is a forecast negative margin. This data does not take into account of the France-England inter-connector which can supply 2GW. Presumably network planning between now and week 50 will ensure that more generation is on-line by then to cover the remaining deficit! The function of this projected data is to achieve this exact purpose – to highlight potential supply shortfalls or oversupplies in good enough time to allow corrective action to be taken.

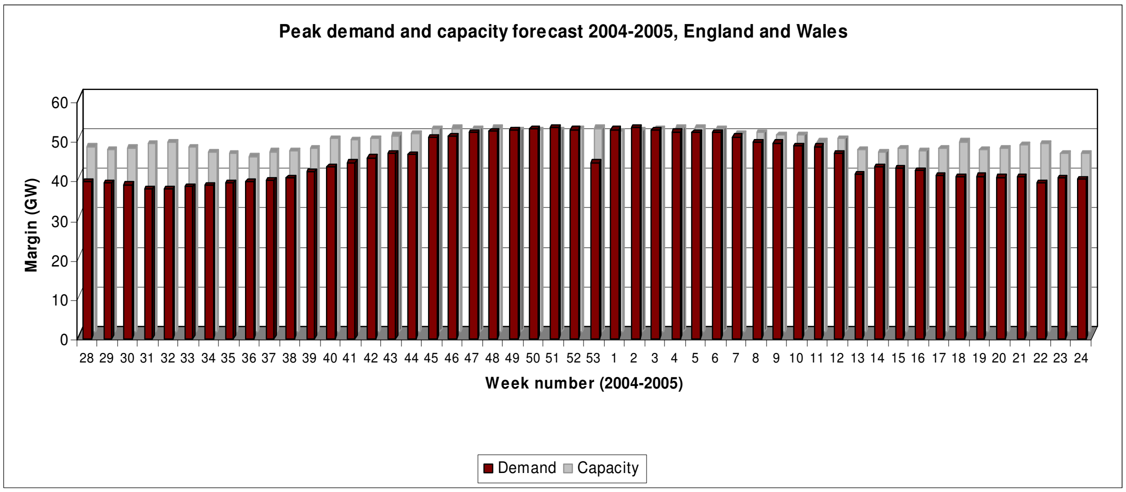


Figure 2-7 Demand and implied capacity forecast 2004-2005, England & Wales

This chart is simply the previous data combined and overlaid to show the implied capacity vs. demand. Capacity varies throughout the year, even though the bulk of the capacity is fossil-based and not constrained by weather. The fluctuations in projected capacity are due to planned maintenance, outages, de-commissioning of old plants and commissioning of new generation.

In a future UK scenario, with much greater penetrations of weather-dependent wind, solar and wave power, it will not be possible to forecast capacity in the same manner. Long-term averages of capacity might be relied upon to certain confidence levels if reasonable large factors of overbuild are used, but short-term availability of wind, wave and solar power will fluctuate with the weather. Renewables can reduce the required fossil-based mean power output but can increase variability. Weather forecasts will play an increasing role, not only in the short, medium and long-term forecast of demand but also in the forecasts of supply. While extreme fluctuations in weather cause modest changes in the percentage energy demand, of the order of 10% (for example a 50 to 55GW shift on a cold week) , weather fluctuations might cause the entire UK wind capacity to operate at 100% or 0%. If wind penetration was 20% of UK capacity, that could mean a 20% drop in capacity on a calm day. These swings in capacity are far larger than any other unpredicted and uncontrollable short or medium-term changes that we currently encounter in demand or generation availability.

2.3.2.2 Price volatility examples, England & Wales, 2003-2004

Presented here are three examples of the price volatility in the wholesale UK electric power markets. The markets are currently operated by Elexon [14] under the NETA [27] arrangements. The situation is not unique to the UK – experience in the US markets has also shown that peak electricity prices can spike up to 1000% of the nominal values during tight margin conditions.

The first two examples were picked by analysing records from the MET office past weather website [32]. The worst cold-weather events across England & Wales during the last two years occurred around the 7-8th January 2003 and the 26-28th January 2004. The England and Wales demand and pricing information was extracted from the Balancing Mechanism website [27] for these periods. As a contrast, demand and pricing was also extracted for a period of warm summer weather in June 2004.

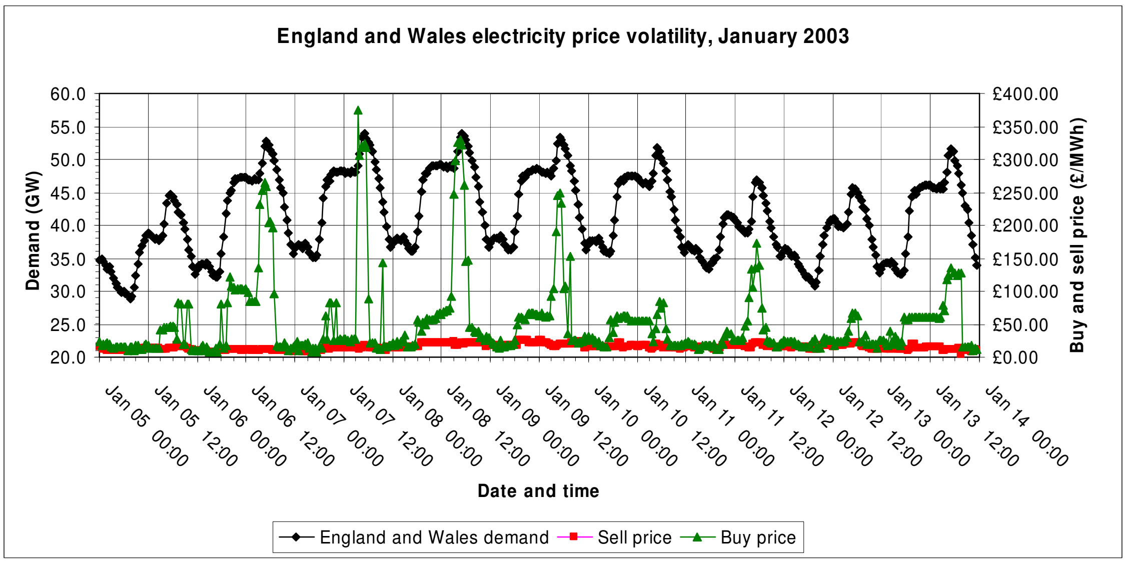


Figure 2-8 England & Wales demand and price volatility, January 2003

In January 2003, a winter snowstorm caused the electrical demand for England & Wales to rise towards 55GW. The data for the exact available generation is not directly available in the public domain. Assuming that there was a 3% margin of supply at the peak 55GW demand, then only 1.65GW more power could be called upon. We can safely assume that the inter-connectors from France and Scotland were already importing their capacity of 2GW each, and therefore any extra supply would have to come from within the UK. There exists in the UK a certain amount of industrial load-shedding that can take place via standing agreements with the distribution networks, but aside from this the demand is inelastic to the diminishing supply-demand margin. Any generator who was able to supply more power at this peak time has a powerful market position to sell power very expensively. In particular, as the figure of 1.65GW is small enough to be within the capacity of a single large coal-fired or nuclear supplier, that supplier might become pivotal.

The wholesale electricity prices, during the January 2003 weather event, fluctuate from a low of £5/MWh to the nominal £15-20/MWh to over £350/MWh.

An additional trend to note is that the 5th, 11th and 12th are weekend days, and have noticeably reduced peak demands due to industrial and commercial use reductions, and changes in the domestic load profiles.

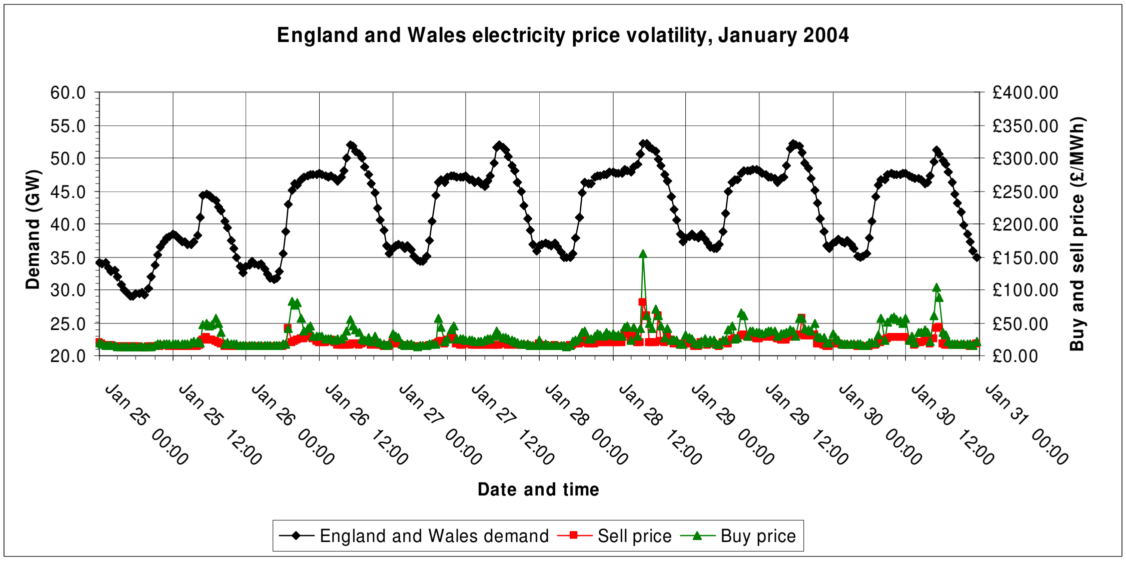


Figure 2-9 England & Wales demand and price volatility, January 2004

In January 2004, another cold weather event occurred. The peak demand was lower that for the January 2003 event, at about 52.5GW, and the peak price of £150/MWh occurred on Wednesday 28th during the snowstorm. Presumably, the required network generation was on-hand and the supply margin was always substantial, as prices remained relatively stable. The prices depend on a number of factors, aside from the weather pattern driven demand. If the weather event is predicted by the Met. office, then the demand forecast for the days ahead can account for it. By raising the demand forecast, more power can be purchased from the generators in advance agreements, leaving less trading to the last minute. This reduces and stabilises the price. Possibly, during January 2004, the weather forecast had predicted a worse weather event than actually occurred. This would encourage a “glut” of power which might be available should the weather event prove milder than expected – leading to oversupply and a short-term drop in wholesale prices. Over-forecasting the demand is not a solution to volatile prices, however; consistent oversupply causes inefficiency and consequently raises the average price over the long-term as generators recover the costs from lost sales.

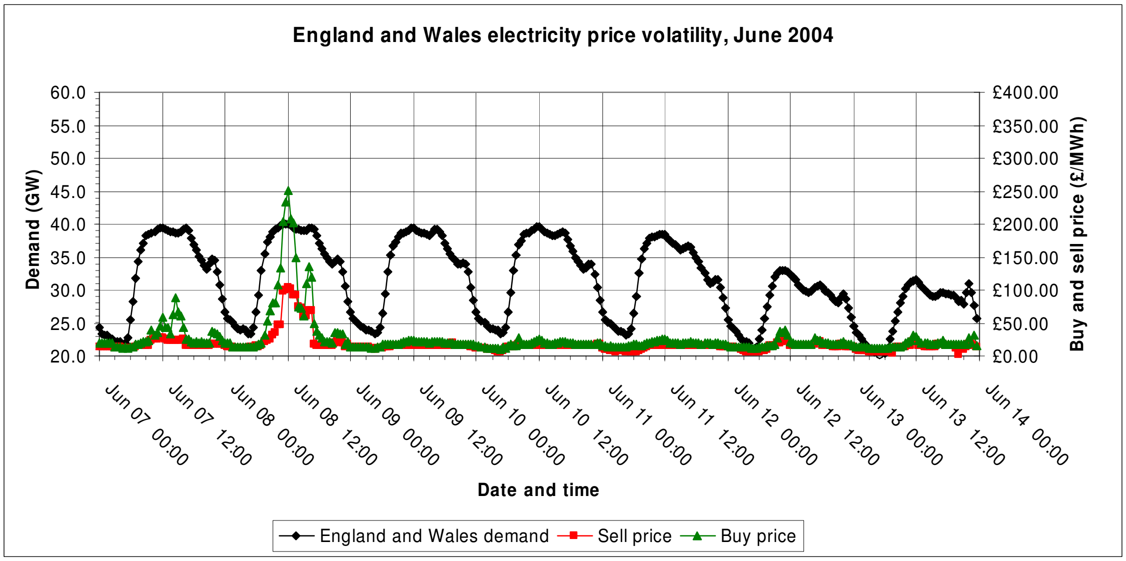
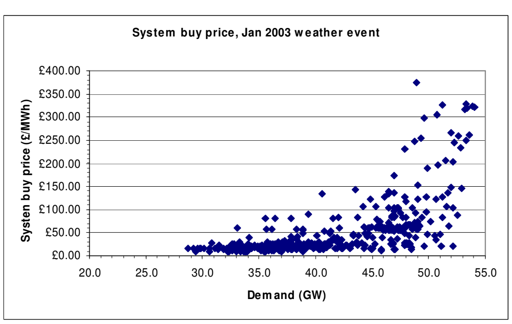


Figure 2-10 England & Wales demand and price volatility, June 2004

The above example was taken from a week of good weather across England and Wales, during June 2004. Notably the peak demand is only 40GW, relative to peak winter demands of 50-55GW. Also, a demand tapering can be seen for Friday June 11th, Saturday June 12th and Sunday June 13th. An interesting event occurred during June 8th, when prices spiked to £250/MWh – higher than the price during the cold weather event of January 2004. Peak demand on June 7th was 39.5GW whereas demand on the 8th just surpassed 40.0GW at 11:30AM. Prices began rising on 8th at 8AM, presumably caused by a new updated weather forecast or an extrapolation of demand to produce a more accurate daily forecast than the previous release. It is possible that the magnitude of the price spike could be linked to a “psychological” barrier at 40.0GW. Demand on the subsequent days came close to, but did not reach, 40GW, and prices were very stable. The total available economic supply to the market that day might be only marginally higher than 40GW based upon the long-term demand prediction for summer months, and the major generator units that are subsequently taken off-line for maintenance or are uneconomic to run during these times.

These prices can be plotted in a way that is more useful from for economic modeling. Plots of price against demand, known as “demand curves” give an indication of the way that prices rise extremely rapidly as demand approaches the fundamental limits of supply capacity.



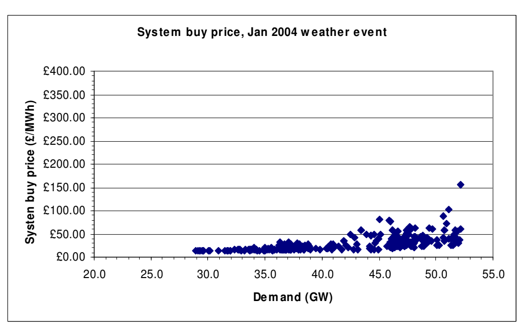


Figure 2-11 System buy price vs. demand; January 2003 and 2004 events separately

Figure 2-11 shows the events of January 2003 and 2004 separately. Although these events caused different demand peaks, they occurred at approximately the same time of year and the amount of generation capacity was approximately the same. When overlaid in Figure 2-12, the two data sets are not visually discernable and can be considered as one. It can be seen that the supply capacity must be in the 55 to 60GW range, and that there is a substantial knee in the curve at around the 48GW, £100/MWh region.

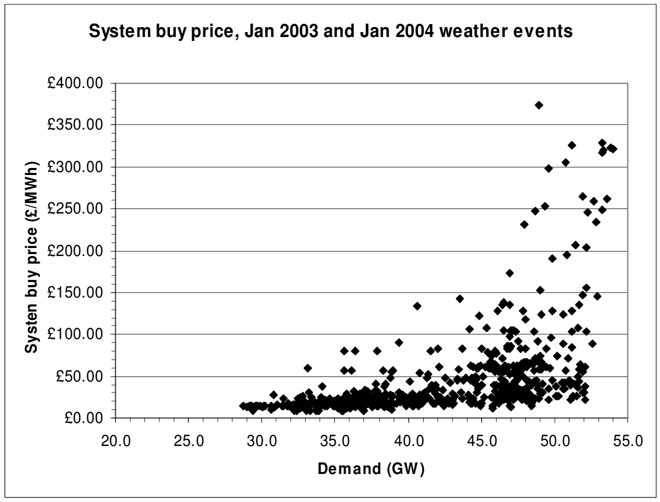


Figure 2-12 System buy price vs. demand; January 2003 and 2004 events combined

Also, there is a considerable spread in the price points for demands between 35 and 55GW. The curve is not tightly defined against the demand alone. The additional factors are the last-minute balancing required which allows aggressive energy traders to drive prices higher or lower, and the effects of energy sellers or buyers who are pivotal, or close to pivotal, in the market at any instant.

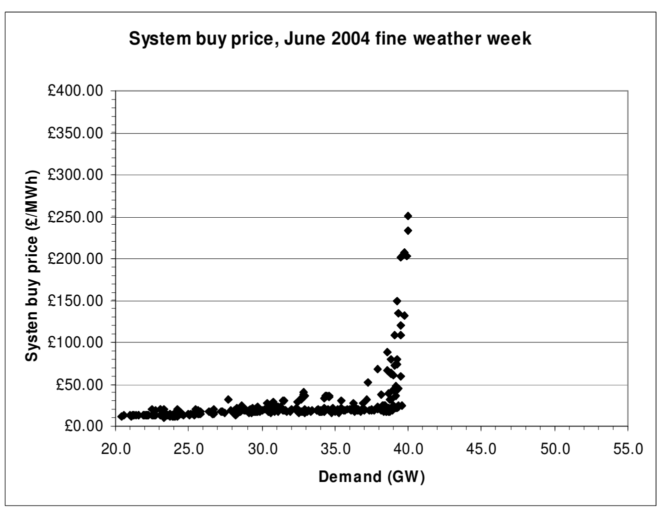


Figure 2-13 System buy price vs. demand; June 2004 fine weather week

An equivalent chart for the summer data is shown in Figure 2-13. This curve is much more tightly defined than the winter data, although it must be remembered that the price spike to £250/MWh occurred on only one day (Figure 2-10) so the data sample around and above the knee of the curve here is rather smaller than for the winter data.

The form of the price-demand curve, for the current inelastic market, therefore depends upon the following factors :-

- The absolute available generation capacity at any time, on a purely technological basis.
- The forecast demand from the weeks, days and hours before. This determines the amount of power generation that can be scheduled and purchased "in advance" in a controlled more fashion.
- The difference between the actual demand and the forecast demand on a half-hourly basis. These differences require power trades at very short notice and encourage volatile prices which can be mathematically chaotic in the same manner as a stock exchange.

In terms of renewables, and the aim of introducing high penetrations of renewable generation, the volatile prices pose a problem. Volatile prices discourage renewables since the renewables are less controllable. Excessive prices are likely to occur when the sun isn't shining or the wind isn't blowing. At these times, fossil-based generation available on-demand can exploit excessive revenues, giving them a biased competitive market edge over the renewable generator who will miss out on the highest-priced electricity sales. Flattening the price vs. time volatility will "level the playing field" somewhat and help renewable generators achieve financial success, independent of external grant funding or compensation mechanisms.

2.3.2.3 The impact of demand response on the price-demand curve

Passing time-varying prices to electricity consumers will introduce a degree of elasticity into the market; this means that higher prices will persuade some or all users to reduce their consumption and vice versa. Demand response will have two key effects on the electricity market. As well as improving the network reliability, by encouraging load reductions as demand approaches supply (via price), demand response will reduce the volatility of the wholesale electricity price.

The effect can be demonstrated by referring to Figure 2-14, which is a simple cost curve model based upon the data in Figure 2-12. In an elastic market, assuming an elasticity of, say, -0.2, demand will reduce by 20% as price rises 100% as described in Equation 1. If demand reached 50GW, the price of electricity would rise to about £100/MWh (10p/kWh). Customers exposed to this price increase over their "nominal" charge which might be closer to £50/MWh (5p/kWh) would, on average, reduce their consumption by 20% due to this 100% price increase. The 20% reduction would reduce demand to 0.8*50=40GW and the price of electricity would drop. If demand remained this low, prices would also lower, and demand might subsequently rise.

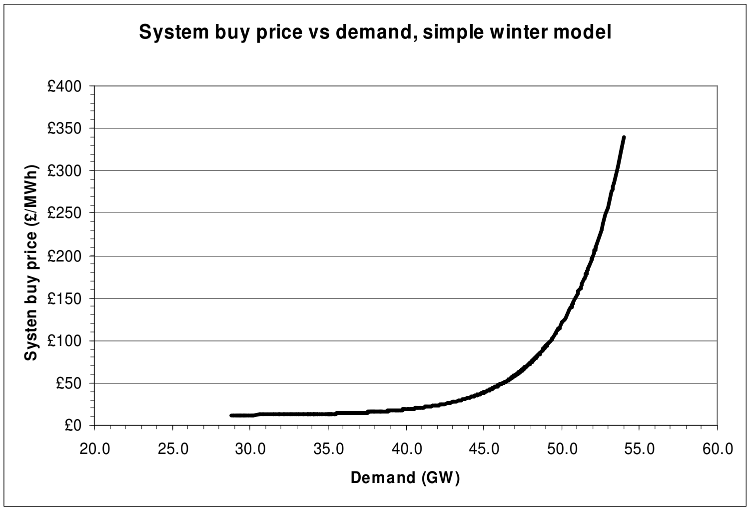


Figure 2-14 Simple model of system buy price vs demand, England & Wales, winter

This "step-by-step" analysis is over-simplistic as the situation would occur in real time on a much more analogue basis. The way that demand, and subsequently price, changes in real time will be a constantly varying pair of parameters, interrelated by the laws of supply and demand. The effect of elasticity will also depend heavily on the method and time-lag with which the demand and pricing information both reaches the customer, and how easily they can or choose to react. Some customer demand reactions might occur in anticipation of price changes based upon fixed time-of-use charges (i.e. economy 7 and white meter), while other customer reactions might to be based upon real-time information or short/medium term notice.

Key points here:-

- The shape of the price/demand curve is directly linked to the maximum generation capacity available, also taking into account transmission and distribution constraints.
- The shape of the price/demand curve rises exponentially as demand approaches the available capacity minus the capacity of the single largest generation company (which will become pivotal).
- Demand only approaches the maximum available supply capacity for very small proportions of the time (Figure 2-3).
- When demand does approach the maximum available supply capacity, only small reductions in demand can produce much larger proportionate changes in price. This is shown by the gradient of the demand curve in Figure 2-14.
- The low asymptote of the demand curve tends to the minimum achievable economic generation price based upon capital plus fuel costs, although occasionally the wholesale price goes below this level due to market forces.
- **The shape of the demand curve will not be modified by demand response activities**.
- Demand response activities simply affect the operating points used on the curve. This is done by market elasticity, by passing on higher prices to customers at high demands,

therefore tending to push demand down. Demand response will tend to avoid operating the price-demand curve in the highest price regions where the price tends to infinity.

- When referring to the demand and price vs. time graphs Figure 2-8 to Figure 2-10, the effect of demand response will be to smooth the demand curve, by lowering the peaks. The troughs will also be filled, as customers will be eliminating some non-essential peak demand (e.g. excess lights), but shifting other more essential demand (e.g. washing machines) to off-peak hours.
- By using the same price-demand relationship without modification, the price vs. time traces in Figure 2-8 to Figure 2-10 could be smoothed. The small reductions in peak demand will remove the largest fluctuations in energy prices, and reduce the price volatility.

2.3.2.4 Regional electricity company revenues, expenditures and profits

The REC (Regional Electricity Company) service providers must pay the system buy prices to purchase the power that is sold on to us. However, as already discussed in section 2.3, most UK electricity customers pay a flat rate for power, independent of time. The exceptions to this rule are some “economy 7” and “white meter” domestic customers, and some large industrial customers who can pay real-time prices for electricity and/or take part in emergency load-shedding activities.

The REC revenue stream comes mainly from fixed-rate standing charges and per-kW charges that we pay. However, the REC financial outgoings for the energy are real-time prices paid to the Balancing Mechanism. Therefore, the REC financial position is inherently risky. Whether they like it or not, the REC is engaged in an energy futures business between us, the customers, and the Balancing Mechanism. If a harsh winter was to occur, the REC companies might have to absorb massive losses due to escalating energy buy prices. To safeguard against this, our fixed-rate electricity is marked up substantially from the £15-20/MWh (1.5-2p/kWh) realistically viable base wholesale price. Domestic consumers pay approximately 7.5p/kWh (£75/MWh) plus a standing charge for connection. The bill includes DUoS fees of approximately 0.7-0.8p/kWh (£7-8/MWh) for daytime and 0.1-0.16p/kWh (1-1.6£/MWh) for economy-7 and white meter electricity [19]. These figures, even after subtracting the DUoS fees which relate to capital network maintenance and upgrade, imply that up to 50% of our electricity bill is markup in distribution and transmission. A substantial portion of this is attributable the “risk premium” that we pay to cover harsh winters.

During mild winters, the REC can profit from the lower energy prices since demand will be lower. As we have seen, since very small reductions in demand on critical days can cause large price changes, the variation in expenses that the REC incurs can be massively dependent upon weather events and human mass behaviour on particular days. In some years, the REC utilities will make massive profits, in the same way as an insurance company profits from our policies. As customers paying fixed rates for power, we are essentially buying an insurance policy from the RECs. So long as Ofgem allows them to charge a high enough charge per kW, and the average price of wholesale power remains low enough, the RECs' profits can be large and positive based on their weather-based derivatives bets. Even during the worst weather events of 2003 and 2004, the average wholesale energy price is only £46/MWh (4.6 p/kWh). During the June 2004 period data, the average wholesale energy price was £28/MWh. These example periods all allow the DNO to continue profitably when the charge to customers is closer to £75/MWh.

Currently:-

- REC revenue stream is largely out of their control – it is fixed by our inelastic demand and the per-kWh charges that Ofgem allow the REC to charge. REC revenue will only increase if they sell more power, but encouraging customers to do this is both politically unacceptable and also risks blackouts (and hence financial penalties) if the uptake is too successful! Hence, REC utilities tend to adopt a neutral stance on issues of energy efficiency, neither encouraging nor discouraging efficiency or increased energy use.
- REC financial expense is a gamble on the weather, generator availability, transmission grid availability, and mass human behaviour. Much of the REC profits and losses are essentially the results of derivatives bets based upon these factors.
- The mass customer market funds the gamble indirectly, via long-term payments substantially above the average energy price.

2.4 Storage technologies and reserve capacity

The implementation of electrical storage technologies can mediate the effects of short and medium-term supply and demand imbalances. Indeed, if electrical storage capacity was virtually unlimited, price volatility would be very low. In this case, electricity prices would change on weekly or yearly timescales dependent upon long-term aggregate energy supplies and requirements. Volatility would be less than current oil price volatility, since UK-based renewable and fossil energy source availability would be largely immune from political situations in foreign countries, and stored energy could ride us through days or weeks of generation down-time or demand surges.

The reality is that bulk electrical storage is extremely difficult and expensive, and will remain so without a major breakthrough in superconductivity or some other currently unknown physical effect.

However, there is an extremely important point to bear in mind. The financial benefit of storage, in a free market, is governed by the highest prices of electricity which occur at times of peak demand and/or supply-demand deficit. Therefore, if the stored electricity is sold at peak periods for costs of £50, £100 or £400 per MWh, but was purchased at £15/MWh, then the financial economics of the storage facility benefit from the revenues that can be generated at peak periods. Care must be taken to include the round-trip efficiency of the storage, since this increases the amount of electricity that must be first purchased in order to release a given amount of energy, and also the difference in wholesale buy/sell prices that NETA offers [20][3].

For example, the Cruachan pumped storage facility might buy 4000MWh of power at £15/MWh over several hours at night, at a cost of £60,000. The next day, the power available for release will only be about 70% of this due to the inefficiencies of pumping and generating. Therefore, during the peak periods of the day, 2800MWh could be sold over 6 hours at 400MW. The sale price at the peak time might be £100/MWh leading to a revenue of £280,000. Net revenue minus expense for the day would be about £220,000. Over a year, £80 million might be generated. Over 25 years, £2 billion. These kind of economic values placed on storage might justify capital investment in either large scale bulk storage, or widespread embedded micro-storage. To obtain these financial incentives for embedded storage, it is crucial that electricity prices are allowed to vary in real time with the supply and demand market. A flat rate electricity price will not provide revenues to justify capital investment in embedded storage schemes.

2.4.1 Reserve capacity types

Reserve capacity on the network is required :-

- To fill in any deficits in the supply vs. demand balance, that cannot be met wholly or effectively by available storage.
- To be available to cover for any unexpected outages in firm generation or network infrastructure.

There are several classifications of reserve capacity:-

- Regulation. Generators online, on automatic generation control, that can respond rapidly to system-operator requests for up and down movements; used to track the minute-to-minute fluctuations in system load and to correct for unintended fluctuations in generator output.
- Spinning reserve. Generators online, synchronized to the grid, that can increase output immediately in response to a major generator or transmission outage and can reach full output within 10 minutes.
- Supplemental reserve. Same as spinning reserve, but need not respond immediately; therefore units can be offline but still must be capable of reaching full output within the required 10 minutes. Hydro and pumped storage can fulfil this requirement with reasonable efficiency.
- Replacement reserve. Same as supplemental reserve, but with a 30-minute response time, used to restore spinning and supplemental reserves to their pre-contingency status.

[3] In 2003, the NETA buy/sell differential was large enough to dissuade pumped hydro operators from trading. Instead, they sometimes chose to leave the network be and let NETA balance the system with CCGT generation. This adds to market volatility.

Reserve capacity is expensive. Spinning reserve and replacement reserve plants (known as "peaking" plants) must be manned and operational, but earn little revenue while not exporting power. Their costs must be covered during potentially short bursts of peak power, or via contracts which reward them for simply being "on-call". Regulation requires that generators operate at less than 100% power so that some is in reserve. Operating at less than 100% power output often lowers efficiency unless the plant is very well designed.

2.4.2 Pumped Hydro

Pumped hydro capacity in the UK is stated to have a maximum peak output of 2788MW [10]. The storage consists of just four bulk storage facilities [10]:-

- Dinorwig 1728 MW, 9100 MWh, 72-78% cycle efficiency [12]
- Ffestiniog 360 MW, 1400 MWh, 72% cycle efficiency [12]
- Foyers 300 MW
- Cruachan 400MW

These facilities can typically only run at full power output for 4 to 5 hours until the upper level reservoir is empty. The facilities can store and retrieve the electrical power at approximately 70% efficiency, so substantially more power must be put in than is recovered. The total amount of energy retrievable is approximately 14GWh, which would be enough energy, alone (assuming the power could be released at any speed), to supply the UK energy demand (370TWh/annum) for about 30 minutes on average. Clearly, the pumped hydro storage that we currently have is nowhere near an amount required to ride the UK through a sustained period of substantial supply deficit. The supply deficit might be caused by a high penetration of wind power and a windless period of many days and/or a severe weather event combined with a lack of available peaking power, be it renewable or fossil based.

It is extremely unlikely that the amount of pumped storage in the UK will increase by any large factor. The lack of suitable sites from technical, economic, political and environmental standpoints makes future large schemes like Dinorwig difficult to imagine. The large bulk storage schemes require heads of approximately 500-600 metres, with suitably large reservoir locations at both the upper and lower levels, and a suitable location for a power plant.

From a smaller scale perspective, within a distribution network, we might imagine small pumped-storage schemes.
The storage capacity of a 10m x 10m x 10m tank of water, suspended 30m above a similar but lower reservoir, would be approximately :-
$E = \text{Volume}.\rho.g.h$
$E = 10 \times 10 \times 10 \times 1000 \times 9.81 \times 30 = 294.3\ \text{MJ} \quad \sim= 82\ \text{kWh}$
$\rho=1000\ \text{kg/m}^3$
$g=9.81\ \text{m/s}^2$

Also, it must be remembered that the energy put into such a tank would in fact be approximately 82/0.84 = 98 kWh and the amount of energy retrieved only 82x0.84 = 69 kWh, since the efficiencies of pumping and retrieving are approximately 84% each, leading to a round-trip efficiency of about 70%.

This amount of energy would (on average) provide the electricity for one household for 5.5 days based upon a current average household electricity consumption per day which is approximately 12.6kW/day based on a UK domestic annual usage of 115TWh and 25 million UK households [8]. The amount of realised storage capacity is not large compared to the number of house-days' worth of electricity served by the rather unfeasible $10m^3$ tank of water suspended 30m high.

2.4.3 Demand response as a storage technology

In effect, any shifting of electrical demand that a customer might make due to pricing signals can be considered as a form of "storage". Activating space heating at different times of the day constitutes storage since the building stores the heat over time. Delaying a washing machine cycle from 3pm until 1am constitutes a release of energy to the network at 3pm and a storage of energy at 1am. What's more, these "storage" efficiencies can be 100% or close to 100% efficient.

If the demand response of the customer to the pricing signals is simply to reduce consumption, without later carrying out that same activity, then the "storage" has an effective efficiency of >100% or even infinity. For example, if a customer simply turns off a light in response to a peak electricity price, the "storage" efficiency is infinite, since no energy input is required at other times to yield the demand reduction at peak time.

2.4.4 Summary of storage technologies

A detailed analysis of potential storage technologies is presented in appendix 7.3. The data is summarised here into a table to provide easy comparisons and a contextual feel for the scale of the energy storage which is achievable, both technologically and economically.

	Bulk storage capacity (proven)	Storage capacity density, per 10m x 10m x 10m cube		Domestic storage feasibility and capacity	Round-trip efficiency	Cost	Plant life	Feasibility
		MWh	House hold-days		%			
Pumped Hydro	14GWh (UK) 1.1 million household-days	0.069	5.5	NO	70-75	££	25+ years	Extremely limited by suitable locations
Lead-acid	Small scale	28	2200	£8000+ for a 5-10 day reserve	85%	££ £60-120 /kWh	10 years	Widespread uptake limited by global lead availability unless electrolyte stores used? May become marginally financially viable.
Heated water	Small scale	98 (heat)	7800	Very cheap. Potential 50% loss per day in summer per day, for a small system.	100% (to heat).	£	25 years	Cheap, simple. BUT, energy must be used as low-grade heat for washing, heating, bathing etc.
Hydrogen	Not yet proven, but potential on a large scale	800 + 800 (heat)	63000	Possible	20% (to electricity). 20% (to heat).	£££	?	In development
Flywheels	Unproven	12	950	?	~60-80% Less for storage times of days (bearing losses?)	££££ £3500 /kWh	25 years?	Problems with bearing losses, mechanical stresses, risk of catastrophic failure.
Compressed air	None	2.3 Efficiency drops to ~17% after one day	180	NO	~64% Less for storage over hours or days.	££		Large pressure vessel required. Temperature losses rapidly reduce efficiency.over time.
Superconductivity	None	0.0015	0.12	?	?	£££££	?	Long lengths of wire immersed in liquid helium. Tolerable magnetic field strengths?
Demand response	?	?	?	?	100% to infinity	£?	?	To be discussed

Table 2-6 Summary of storage technology potentials

The conclusions are fairly simple. Pumped hydro works well in large schemes but there are few or no UK locations remaining. Although pumped hydro dominates our current storage capacity, it is still only equivalent to 30 minutes of average UK electrical demand. Pumped hydro is not effective at small scales, as the energy density is too low. Fundamentally this is because the force of gravity is weaker by orders of magnitude than the other physical forces of electro-magnetics and molecular bonding. Superconductivity and compressed air fail to produce appreciable energy storage densities due to constraints of electro-mechanical and thermodynamic laws. Flywheel storage can store limited amounts of energy, if expensive composite materials and high specification bearings can be used.

Lead-acid batteries store energy reasonably densely, due to the chemical bonding nature of the energy stored. Their uptake might become marginally financially viable in the near future, but widespread deployment might be limited by the global reserves of lead and possible lead market price rises. Electrolyte stores might get around the lead problem, and could also avoid the requirement to space the batteries at 1/3 battery to space ratio, since the electrolyte could be stored in relatively maintenance-free tanks. The batteries power-cells themselves require maintenance and probably a replacement/refurbishment scheme after 10 years.

Hydrogen storage, which stores energy via chemical bonds, represents very good energy density and the liquid hydrogen is also transportable by reasonably conventional means. The downside is the relative immaturity of the technology (which can be overcome), but also the relatively poor electrical round-trip efficiency which is only 20%. Heat is also released at about the same rates and can be used if heat loads are nearby. It is unknown whether hydrogen electrolysis might be acceptable in a domestic environment in the future.

Simple, low-tech heating of water stores energy in larger energy densities to a lead-acid battery store (at 1/3 battery to space ratio). Water heating requires very little capital expense – there are no pressure vessels and the heating element is a simple resistor. Suitable insulation must be used but this is relatively cheap. The downside is that the energy cannot reasonably be reconverted to electricity. It must be used (or lost) as heat in or near the energy store. Small domestic stores, depending upon the size and insulation, lose energy via conduction relatively quickly over hours or days. This energy storage efficiency loss can be minimised by sizing a tank appropriately for each dwelling or group of dwellings, and investing in insulation.

2.5 Summary of drivers for demand response

The drivers for demand response are:-

- That there is currently no closed link in the supply vs. demand cycle for electric power in the UK.
- The resulting market inelasticity causes volatile prices.
- The market inelasticity means that there are very few real-time tools for reducing demand in times of poor winter weather or when supply is otherwise constrained.
- The fixed price electricity which we buy does no encourage awareness of energy efficiency or of the real-time difficulty of supply and demand in the electricity industry.

- The REC companies currently stand to make a large proportion of their profits from the derivatives trading surrounding the "premiums" that we pay against the risk of harsh winters. Since these energy trades were the kind of business that Enron were involved in, having divorced themselves from the actual business of operating networks, it is reasonable to suggest that our REC and DNO companies should be concentrating on running efficient networks and security of supply. Their revenue stream should be based around quality of service and efficiency; they should not be primarily engaged in the business of energy futures to generate their profits.
- As customers, although wholesale energy prices are at all-time low prices in real terms, we are not able to participate in the use of off-peak electricity prices, apart from a few users of economy-7 and white-meter schemes.
- Fossil fuels are running out, or becoming suspect from a security-of-supply viewpoint. Nuclear fission is not yet proven. Nuclear fission will only last 300 years (less if the Far East increases consumption), unless fast breeder technology is adopted and this is politically unacceptable at the current time. Our energy must increasingly be sourced from renewable supplies and these are weather dependent. Weather-dependent sources by their nature are variable and uncontrollable. Without substantial overbuild, vast bulk electrical storage would be required and this is not currently viable due to technological, financial and efficiency constraints. Consequently our available supply will become more variable, and therefore our electrical demand must begin to adapt to the changing supply. This can only happen if the supply-and-demand cycle is completed by passing prices to customers.

2.6 Detailed objectives of this paper

During this paper, we will investigate the effects that demand response and embedded storage facilities might have on the UK electrical power grid. The demand response involves a large social change, whereby individuals or businesses modify their consumption patterns based upon pricing signals from the power markets, or merely via voluntary actions. We will investigate in depth the potential for manual and automatic demand-response mechanisms in the domestic sector, while also considering the commercial and industrial environments.

The demand response may consist of any combination of the following three intertwined actions, either by manual conscious decision or by some automated system:-

- Energy reduction at times of peak electricity price (peak clipping)
- Shifting of energy consumption from peak to off-peak times (valley filling and smoothing)
- Embedded and domestic storage schemes activated by peak and off-peak pricing signals (smoothing)

First, we conduct a review of available methods of achieving demand response. This includes the technical, financial and social issues surrounding the passing-on of electricity prices to the general population. Also, we review the estimated elasticity of demand for the domestic, commercial and industrial sectors from available literature.

In chapter 4 we present a novel analysis tool with which we can generate and present demand-response simulations which combine estimated market elasticities, UK energy consumption data, estimated human behaviour factors, weather data, storage technology data, and a model of electricity pricing in the UK. The outputs of the simulator are baseline (without demand response) and new (with demand response) demand and price profiles for the UK power network over chosen time periods and weather events. The aim of the simulations is to find realistic demand-response and embedded-storage implementations that modify UK electricity demand to fit a variable, weather-dependent generation portfolio, while not requiring any more bulk pumped-hydro storage capacity than we currently have. Simulation results are presented in chapter 5.

3 Demand response methods and technologies

The Demand Response and Advanced Metering Coalition [7] quote information from the California Energy Commission. The claim they make is that building peaking power plants to cope with peak demand costs $600 per kW, while demand response measures only cost $100 per kW to implement. This statistic alone, if accurate, is enough to justify the development of a widespread demand response programme.

Currently, in the UK, there are only limited methods via which demand response may occur in the electricity market.

- “Pre-agreed” load-shedding in the industrial sector
- “Economy-7” and “White-meter” split day and night-time metering
- Emergency load shedding by the DNOs (this is a last resort and leads to some non-essential customer’s experiencing an unplanned blackout)

This chapter will detail the existing and potential methods by which demand response (including non-bulk storage) can be triggered by the balance of supply and demand, and the pricing signals given from the balance. The first discussions will involve established demand response methods, and then move on to emerging and then untried systems. Also, the technical feasibility of the schemes will be discussed. At all times, the positive and negative fiscal, technological and social factors must be borne in mind.

3.1 Industrial load curtailment measures

In the industrial sector, where individual customers can consume many hundreds of kW, load curtailment has been a common practice for many years. The methods are established, although the exact details of the contracts and the fiscal incentives have changed since privatisation of the power networks.

Load curtailment in the industrial sector happens via pre-agreed curtailment contracts. Businesses must sign up in advance, and renew the agreement periodically. The agreement specifies the amount of load that can be shed, the notice period that must be given, and possibly the minimum and maximum number of times per year that the curtailment might be required. The agreement might be with the DNO/REC directly or via an intermediary CSP (Curtailment Service Provider) company. For the largest customers connected to the transmission grid, the CSP might in fact be the Balancing Mechanism administrator itself.

If demand approaches supply, the CSP can contact the business and give the required notice by phone or other real-time communication method. The load that the business sheds is “bought back” from the business at the maximum of either:-

a) The market rate for electricity, or

b) Some fixed amount, dependent upon the amount of notice given

If the business fails to shed the load, a fiscal penalty of some form is imposed by the CSP. There are many forms of penalty, from simply fines to withheld future payments of "capacity credit" payments. Large customers partaking in the curtailment schemes can qualify for "capacity credit", as they essentially count as reserve generation. The credit is a financial incentive to join the scheme. The capacity credit magnitude varies with location, being larger in areas where generation is sparse and lower in areas where generation is plentiful. Referring to Figure 3-1, the capacity credit in Cornwall and the area West of London would qualify for the high capacity credits, while Scotland would not. A more detailed network diagram would highlight smaller localised areas of over and undersupply.

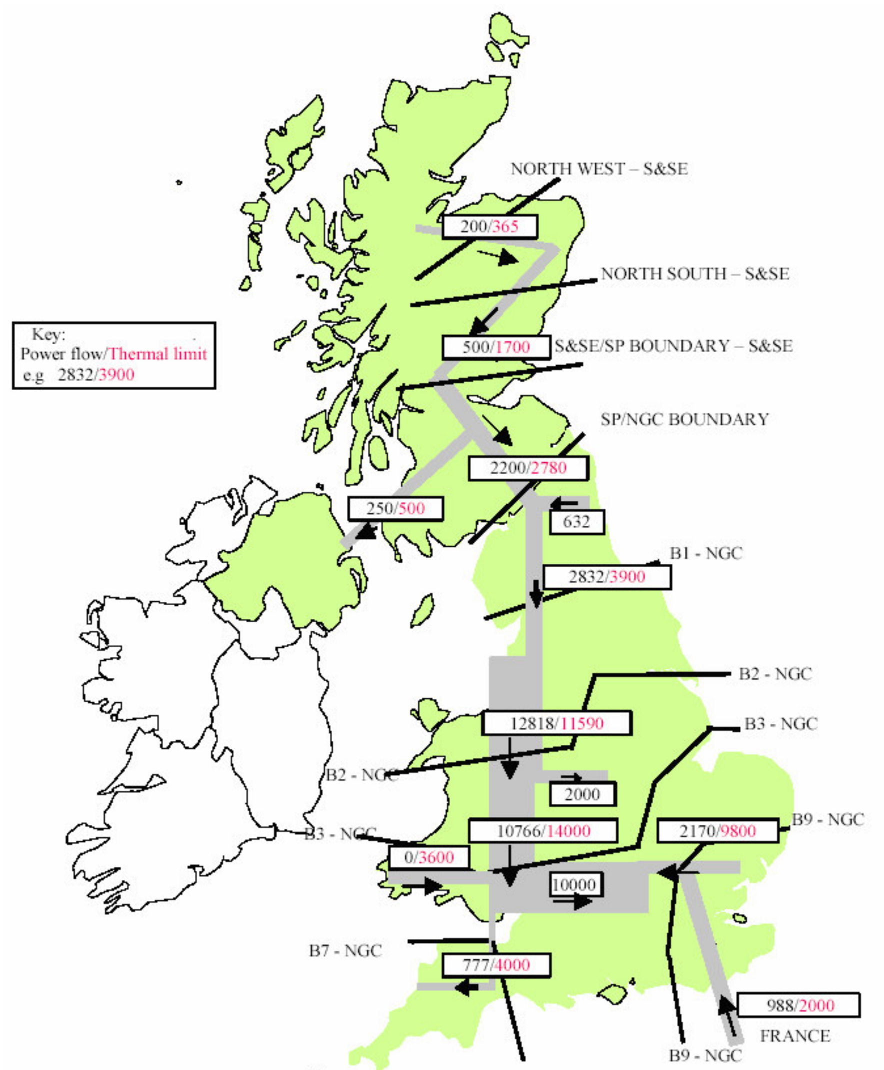


Figure 3-1 Forecast average UK power flows, 2006-2007, in MW [25]

The NEDRI report [26] describes recommendations for two types of industrial load curtailment plans. One is a real-time plan, and one is a day-ahead plan. The real-time plan has 2 available notice periods: 30 minutes and 2 hours. The minimum price that the curtailed power is bought back is proposed to be $500/MWh and $350/MWh for the 30-minute and 2-hour plans respectively. A previous scheme charged an annual fee of $5000 from each participant, and required an aggregate 1MW load size to be eligible. To boost participation, NEDRI recommend that the signup fee be reduced to $500 per annum, and the threshold for eligible load size be lowered to 100kW.

NEDRI [26] recommend that the CSP take a 30% cut of the financial transaction between the system operator (the Balancing Mechanism in the UK) and the customer for the bought-back energy, while the remaining 70% of the transaction value is passed to the customer. The minimum energy buy-back prices above are designed so that the 70% cut which passed to the customer is still a large enough incentive to encourage participation, while also providing a large enough incentive for the CSP to run the scheme efficiently.

For the day-ahead plan, the businesses get the opportunity to bid daily the amounts of load that they will curtail on the following day. Again, NEDRI had a plan existing but the minimum bid size was 1MW, and they recommend that this be reduced to allow smaller users to participate. This method requires a reasonable forecast of 24-hour-ahead supply and demand, but enables businesses to plan the load curtailment better. It also encourages competitiveness and stability in the energy price – so long as the supply and demand forecasts are accurate. For a day-ahead programme to work well, with weather-dependent renewable generation, the weather forecasts will need to be accurate enough that the wind, solar and wave power available can be forecast to a reasonable degree.

The real-time and day-ahead programmes require at least one dedicated person to be responsible for the daily activities at each participating business. Smaller energy users might not be able to afford this manpower, and instead might like to participate in a weekly or monthly ahead bidding programme. This would require accurate forward forecasts of supply, demand and weather over longer time-spans and might be hard to delivery effectively on an accurate basis, although overall known annual cycles of average supply and demand can be known reasonably well.

Some of the industries that curtail loads will not simply go without power. In many cases they can instead use a standby generator to make up the power required to keep operations running. In real emergency periods, the emissions from these generators are not terribly important. However, if load curtailment is to become more common on a daily or weekly basis, it becomes more important to ensure that the on-site generators do not pose a health risk to nearby residents or workers. In general, any industry signed up to a load curtailment programme will be monitored by an environmental organisation (e.g. SEPA) to check that the generator emissions are within acceptable limits. The data containing times of load curtailment events and the participants involved is passed from the CSP or DNO to the environmental organisation.

3.2 Large-scale industrial real-time power pricing

Industrial customers above reasonable thresholds of demand can already choose to participate in real-time pricing of electricity. Some of these customers are large enough to be connected to the transmission grid at HV, and therefore have no dealings with the DNOs and RECs. Others are connected via the DNO/REC at MV distribution voltages, but consume sufficient power to warrant partaking in such a scheme. Up to the present day, the threshold of power consumption has been large, and another significant factor is that the business must be able to justify at least one dedicated person working pretty much full-time on the energy purchasing activity. Essentially the business buys and sells power at market rates, thereby obtaining cheap power at wholesale prices plus a small TNUoS or DUoS markup. The industry takes on the risk of the fluctuating energy prices, but does not have to pay a "premium" to the RECs like the rest of us. Unlike curtailment contracts which are dispatchable by the network operator, in a real-time pricing contract the industry can choose to reduce power consumption at will. It is possible to be in a curtailment contract at the same time as a real-time pricing contract.

Some industry customers find that taking all the risk is unacceptable. Instead, they might agree to purchase some quantity of power in advance at fixed prices, and then buy (or sell) the balance of energy due to their actual usage at real-time rates. Different customers can negotiate different prices for their fixed-rate power due to their daily and seasonal average load profiles which will be known to both them and the supplier (since they have historical data from metering by the hour or half-hour). The customers can make this deal with an REC or balancing mechanism directly, or they can use a completely separate hedging company which is set up solely for this power trading purpose. These hedging companies are purely dealing in energy derivatives. They attempt to make profits by setting the fixed rates slightly above the average energy price over the future period, taking into account the risk factors that they anticipate. (In the current domestic market, RECs are simply hedging companies for domestic customers).

Another, softer method of hedging involves an agreement where the customer has a price cap placed on the purchased power. The customer must pay an agreed fee to the hedging company, but the hedging company will make up any difference between the capped price and the real-time price if it subsequently exceeds the capped limit.

3.3 Voluntary non-fiscal methods

Although any form of quantification is difficult, the effect of purely voluntary changes to user demand profiles should not be forgotten. In a "wartime" environment the public attitude might be to reduce peak demand for the good of the country. In a more modern environment, some people will alter their behaviour simply because they know (or believe) they are doing something good for the environment, despite any fiscal reward for doing so. An example is the recycling of glass, tins and paper. We receive no reward for doing so, in fact it can be a relatively unpleasant task standing at the skip throwing the stuff in. However, across all classes of people there is a reasonable uptake in recycling, on a purely voluntary basis.

So, in the remainder of this report, although it will be hard to quantify, every time that a fiscal method is proposed as a demand response mechanism, we should not ignore the factor that some people will modify their behaviour with or without the fiscal reward. Any measured or assumed demand elasticity will include some amount of purely voluntary action on the part of the population.

The key point here is that people must somehow be aware that it is “better” or “worse” to use electricity at different times. Currently most people have no notion that time-of-use of electricity could ever be important, let alone when those times might be.

Beneficial changes to the electrical demand load profile can be made by promoting voluntary demand response. To do this, the information has to be disseminated. This could either be via pricing methods, or via some much softer option. Such an option might be a daily report of supply-demand balance in the news, similar to the pollen-index and ftse-100 updates that we get regularly these days. We could be informed when and how severe the peak demand periods are likely to be and on each day, and we could avoid those times. The severity could be simplified to a scale of 1 to 5, say, with 1 representing plenty of supply and 5 representing a close-to-emergency situation. When the severity reached 4 or 5, the bulletins could be played more often on the radio or TV with updates in real time, so that people know when the situation has returned to a lower level.

3.4 Fiscal methods in the medium use and residential sectors

This section deals with customers whose load demand is small enough that it does not warrant consideration for a dispatchable curtailment agreement with a CSP, and customers that do not wish to be actively trading energy on an hourly or half-hourly basis. Generally, this applies to all customers whose load is less than 100kW. Although these customers are unlikely to want to actively trade in energy via phone calls and financial transactions every hour or half-hour, our quest here is to find demand response methods which can enable them to be influenced by, and influence, a market whose supply and demand balance changes with the time of day, weather and season.

Demand response at the medium-size and residential consumption levels requires a social change and a new attitude to electricity consumption. The question is; how to achieve this without appearing to infringe on “human rights”, and how to achieve demand response in a politically acceptable manner. The New England Demand Response Initiative (NEDRI) report [26] is a detailed examination of the practical issues surrounding the implementation of fiscal demand response schemes for medium-sized and residential customers. These schemes and issues are summarised here.

To enable most of the demand response methods, an advanced meter (AM) is required.

3.4.1 Advanced metering techniques

A traditional domestic or small-business electricity meter simply measures the real power consumed over time. The meter is typically read every few months and a customer bill generated by applying a flat rate to the power used. There is no information recorded concerning the time pattern of the power usage.

An advanced meter (AM) records the power consumed during much shorter time intervals, forming a list of values which describe a customer's load profile on each and every day. Half-hourly readings are typical. Due to the amount of data generated, it is no longer realistic to collect the meter readings by hand, so electronic means are used. The meters communicate to a utility central computer system via a secure method, of which there are several choices:-

i) Internet (via home computer)
ii) Internet (via LAN of ISDN connection)
iii) Phone line (via internal modem)
iv) Internet (via LV electric lines)
v) Short-medium distance radio.

Since large-scale uptake of demand response requires large-scale uptake of advanced metering technologies, iv) and v) have the big advantage of not requiring any additional fixed-line communication installation. The meter simply needs to be installed in place of the existing meter, by connection at the user's power entry point(s).

Most of the major meter manufacturers are now offering advanced metering products. Elster's new A3 Energy-Axis product is a typical example [15]. It offers two-way communication by phone line via an internal modem, which provides a communication for rural, remote and "base-station" installations.

The A3 meter also offers two-way digital communication in more urban environments via unlicensed 900MHz radio band. Each meter installed can act as a repeater station, relaying information from one meter to the next and forming sub-networks of up to 1024 meters. Each sub-network requires just one meter to be connected to a phone line to complete the communication link with the utility computer. In this way, the transmitted and received power levels to and from meters can be very small, and reception can be arranged even in the most tucked away of meter locations.

In the UK, the electricity and gas utilities have access to unlicensed radio bands via the JRC (Joint Radio Company) [21] which manages the radio spectrum available to these industries. In the UK, the band 183.5-184.5 MHz is currently allocated for automated meter reading, but other frequency ranges are also available to the utilities. New frequency ranges might be arranged by agreement with the DTI. Relatively little bandwidth would be required for these communication schemes, since the meters will be communicating over relatively short distances within the sub-networks, and the amount of data is small (relative to voice communications). The communication requirements are similar to several mobile-phone text messages being sent from each meter to the central computer each day, and several broadcasts from the central computer to all meters each day. Each message would be a single burst of maybe a hundred bytes, compared to voice communications which require constant streams of hundreds of bytes per second.

Historically, the costs of advanced metering have been the major technical barrier to the uptake of demand response. DRAM California [7] now claim that the purchase and installation costs of an advanced meter (AM) can now be as low as $50 and $50 respectively, implying a total installed cost of just $100. This is a significant development in the feasibility of AM uptake.

Features which are required (or highly desirable) in an advanced meter to facilitate demand response are:-

- Simple replacement or retro-fit of existing meters
- Half-hourly recording of power usage
- Ability to transmit lists of half-hourly data to utility computer, at its request
- Ability to transmit data concerning loss of mains (blackouts) and islanding during fault conditions
- Ability to receive TOU periods, charges and updates from utility computer
- Ability to receive critical peak pricing time and charge information from utility computer
- Ability to receive real-time pricing information utility computer
- Wireless communication with a user-interface panel in an accessible location within the building
- Audio-visual warnings from the interface panel during critical peak pricing events
- Programmable audio-visual warnings when user-settable real-time pricing thresholds are surpassed
- Visual indication of real-time prices, TOU rates, schedules, forecasts etc.
- Wireless communication with appliances such as washing machines, fridge-freezers, immersion heaters etc.
- Ability for users to program appliance schedules and cost driven go/no-go & buy/sell thresholds via the interface panel

3.4.2 Time Of Use (TOU) pricing

Time Of Use (TOU) pricing revolves around a number (generally 2 or 3) “fixed” time periods each day at which different known charges apply. The time period may be completely fixed, or may be varied periodically with notice sent to customers. The Economy-7 plan in England & Wales uses 2 fixed TOU periods, peak rate (8am to 1am) at about 7.5p/kWh, and night-time rate at about 3.5p/kWh (1am to 8am). The Scottish “White meter” scheme offered a similar scheme, although the night-time rate could change within certain limits every day; the night-time rate being broadcast over long-wave radio. Disappointingly, the “White-meter” scheme is no longer open to new applicants.

More advanced schemes might use 3 periods. The periods of peak, mid-rate and bargain-rate electricity might be adjusted 4 times a year to account for the different patterns of consumption each quarter as the seasons change

The advantage of a TOU scheme for medium and small customers is that the rates are 100% predictable, save for slight adjustments and re-learning that each customer must do each time the periods change significantly. Customers can set immersion heater timers, washing machine cycles, and other power-intensive activities to occur at known times each day.

The biggest disadvantage of TOU alone, compared to other demand response methods, is that it does not allow updates on a daily basis. In terms of our quest to create a demand response to weather-dependent generation capacity that varies by hour, day and week, TOU helps to modify the general load profile on a statistical basis, but does not provide a full solution. The supply-demand cycle has been closed, but with a filter that allows a seasonal but not a fully dynamic demand response.

3.4.2.1 Inverted block rates

A cut-down version of TOU pricing can be implemented if advanced meters are not available at customer sites. The method requires an estimation of a customer’s actual daily load profile. In the absence of real half-hourly or hourly meter data from each customer, the profile might be guessed by taking higher-level load profile results from within the distribution network, possibly for an entire town, substation or residential neighbourhood.

The “inverted block rate” system has been used in the US (Arizona, California, Idaho and Washington states). The average daily load profile of a residence is calculated from aggregate data. Electrical load peaks in these American locations occur during summer early afternoons, due to air conditioning loads. Since, in general, wealthier residents possess air conditioning, and these residents also use more power on average, the power company concludes that poorer residents have lower overall power usages, less air conditioning and therefore also their daily load profile peaks less during these summer days. In an “inverted block rate” scheme the DNO or REC charges a higher price per kWh to residents who use more power and vice verse, which is completely reverse to normal marketing techniques. This higher price reflects the way that the REC believes that the richer customer's load peaks correlate with system peak demands.

Such a scheme is obviously contentious since many residents might feel that the data does not apply to their personal habits. Moreover, in the UK, it is unlikely that such a scheme would be justified since our peak demands do not stem from such obviously wealth-related luxury devices such as air conditioning, but more from water-heating, space-heating, cooking and kettles which are cross-class necessity activities.

3.4.3 Critical peak pricing (fixed and real-time)

Critical peak pricing could be invoked for any customer with an advanced meter installed, that can receive real-time instructions from a DNO, REC, or CSP. The action would be triggered at similar times to those when the CSP requests large scale curtailments from heavy industry, when demand is dangerously close to available supply.

When invoked, for a participating customer, the information would need to be conveyed to the customer. This could be via a meter repeater panel in the residence or business, situated in some common area where it can be easily seen and heard. An audio alarm would be a sensible feature. Preferably, at least 30 minutes or more notice should be given, plus some indication of the likely duration of the critical peak price. Once the critical price kicks in, the customer would be charged either the full real-time half-hourly market rate, or some fixed critical peak rate, until the end of the period.

If critical pricing was rolled out to the domestic population of the UK, critical pricing would be an important communication mechanism to make the public aware when supplies are short. Aside from the price-based decisions that some people would make, a certain amount of any demand elasticity due to this scheme would be due to a "voluntary" response. No matter how wealthy the individual, curtailing demand at these peak times decreases the likelihood of blackouts – blackouts which cause disruption to poor and wealthy alike. Some of the curtailment will be done to save money, some will be done to be "good to the environment", and some will be done in the hope of avoiding blackouts if others also curtail their demand concurrently.

3.4.4 TOU combined with critical peak pricing

TOU and critical peak pricing can be combined to operate as concurrent and complimentary programmes, where both schemes are unmodified except that critical peak pricing takes priority over the TOU timed events.

3.4.5 Real-time pricing

The half-hourly market prices could be passed back to customer meters in real time. If necessary, the market prices could be moderated by capping the peak price to a regulated level, and adding a small premium to the off-peak rates to compensate. Customers would be able to view the current price and an estimation of the price over the next 24 hours or more. Customer demand would then be elastic as the population would then make valued judgements about which tasks to carry out given the current price. Customers could program their meters through a simple panel interface, possibly to emit audio-visual warnings when user-configurable price thresholds were breached (or forecast to be breached). The programmable interface could also allow for control of immersion heaters, washing machines, fridges etc. which could all have their behaviour modified (if the customer chose) to avoid purchasing the most expensive power.

3.4.6 Demand-side active management

While larger customers can be part of dispatchable load curtailment programmes, smaller customers enrolled in real-time or critical peak pricing schemes could develop their own load curtailment rules. For example, people could program their washing machines; instead of starting a cycle immediately in the afternoon or evening, the machine could be requested to wait until the price of electricity crossed below a certain level and was forecast to stay that low for the required period to complete the wash. Immersion heaters could be programmed the ways such that most power was purchased at cheaper times. The customer could set up slightly more complex programs that would delay activation as above, unless a certain time was reached, and then the activity would start anyway. This would be useful to ensure that a wash was complete or water was hot for some deadline time. Other examples include:-

- Fridges and freezers could be programmed to deactivate for a configurable amount of time (say 2-3 hours) at times of critical peak prices. The time allowed would be defined by the heat capacity of the fridge, to ensure that food did not spoil and freezers did not defrost.
- Computers in an inactive state (i.e. in standby or after the monitor has entered a standby state) could save all relevant data and power down completely.
- Electrical fan and wall heaters could be programmed to deactivate at times of high prices.
- In general, conventional lighting circuits could not be part of an automated active management scheme, due to obvious safety concerns. However, buildings with motion-sensitive light circuits could adjust their mode of operation to reduce the latent time that lights remain on after triggering during peak prices.

All this can be technologically feasible using an advanced metering and some intra-building communication system. In a domestic environment the Bluetooth wireless protocol, or similar system, provides a solution for communication between domestic appliances and the advanced meter. Assuming all the user programs for load curtailment were entered via the meter interface panel, the meter would make all the minute-to-minute decisions which would mean that the only appliance intelligence required would be to pass a “request for start from appliance X” to the meter, and to understand a simple “go/wait/no-go appliance X” signal from the meter. Each participating appliance would need two “on-off” switches; one meaning a definite user input for "on/off" which would ignore the meter and electricity price, and one meaning "go, but only if the meter says so".

3.4.7 Social factors involved with real-time pricing schemes

These kinds of changes might have noticeable effects on average people's lives. Some people might embrace the change and some might hate it. Some people might have enough money not to care, some might have lots of money but care about the environment and enjoy the change. Particular care would need to be applied with the introduction of such schemes, however. In the UK, since so much of our domestic energy demand is space heating, we need to be careful not to add to the problem of "fuel poverty" in households where money is short. Schemes might need to be introduced on a voluntary basis, or with exemptions for the retired, infirmed or poor.

Both the DRAM coalition (California report [7]) and Baladi [4] explain the results of experiments in the USA examining the impact of forced vs. voluntary enrolment in a TOU scheme. The hypothesis was that people who volunteered for a TOU or real-time pricing scheme would do so because they believed that they would benefit from lower bills, while those that did not volunteer believed that they would suffer from higher bills on the new scheme. The experiment involved installing advanced meters in all houses so that use could be monitored. Volunteers were requested, but only about half the volunteers were actually enrolled on the TOU scheme; the remaining volunteers formed a control group. The analysis of the data from the non-volunteers, the control group and the volunteers on TOU shows that there was no statistical link between volunteering and energy use profile before signing up to TOU. Volunteers or non-volunteers might have believed that they would, or would not, benefit from TOU pricing. But the evidence suggests that across the broad population, all households can benefit from real-time and TOU pricing to approximately the same degree. These are important results if true, since they form a good argument for TOU and real-time pricing to be socially inclusive. Additional data from a similar study in the UK would be extremely useful, since it is vital that such schemes are understood by the population to be socially inclusive tools rather than discriminatory methods.

3.4.7.1 Cost estimates of common household electrical tasks

The table below gives an indication the costs of some common household electrical loads.

Task	Power (Watts)	Time (Hours)	Energy (kWh)	Cost (pence) @ 7p/kWh
Shower for 10 minutes	9000	0.15	1.35	10
Bath			5	35
120 litre immersion tank kept warm at 55°C for 24 hours, 1cm insulation thickness	200	24	4.8	34
Hairdryer for 10 minutes	2000	0.15	0.3	2.3
TV/Video on for 2 hours	400	2	0.8	6
TV/Video on for 12 hours	400	12	4.8	34
TV/Video on standby for 24 hours	9+9	24	0.4	3
Computer + VDU on for 12 hours	400	12	6	34
Washing/Dishwash cycle	2200	1	2.2	15
100W lightbulb for 6 hours	100	6	0.6	4
4x100W lightbulb for 6 hours	400	6	2.4	17
100W lightbulb for 24 hours	100	24	2.4	17
Microwave for 5 minutes	700	0.08	0.06	0.4
Kettle for 2 minutes	2200	0.03	0.07	0.5
Hob for 15 minutes	2000	0.25	0.5	3.5
Lighting per day*			2.0	14
Cold appliances per day*			1.9	13
Cooking per day*			1.8-2.2	13-15
Brown appliances per day*			2.9	20
Wet appliances per day*			1.4	10
Space heating*			16.9-30	120-210
Water heating*			10-15	70-105

* these figures are average figures for all UK houses, per day, over 12 months between 2002 and 2004, based upon DTI data quoted in Table 4-1.

Table 3-1 Relative energy prices of common household tasks using electricity

Clearly, space heating and water heating cost us the most money. On winter days, space heating will cost more than this figure, and on summers days the space heating may be zero.

How our demand might vary with electricity price-per-kWh will depend upon our concept of the value of a particular activity to us, against the price it costs. With regard to the above table, it is useful to consider the effect of a 2x to 5x price increase in price-per-kWh during a period of peak demand.

People would probably like to reduce space heating and water heating demands, but this may be difficult since it would still be regarded, even at prices of 2x to 5x current rates, as a necessity rather than a luxury. We would expect elasticity to be low. Some kind of storage here is the most sensible option so that the total energy use remains the same but the demand is moved to a cheaper time.

In contrast, brown appliances and lights are more of a luxury good, commonly left switched on by us when not needed. In these cases, elasticity is more likely.

These concepts will be used when setting up the simulation tool in section 4.12.1.

3.4.8 Regional electricity company effects

Demand response can result in an overall reduction in energy use. Under current REC revenue structures, this can result in lower REC profits. The RECs currently have no incentives to encourage energy reduction. They do, however, have an incentive for load curtailment and demand response measures, since at peak times they will have to sell less power at fixed rates while buying it on the market at peak-time rates. The implementation of an effective portfolio of demand response tools ought to remove the risk from the REC financial position, and one might imagine that the REC would embrace this with open arms.

The truth is that, as described in section 2.3.2.4, the RECs currently make money from being the hedging agents in our current energy purchases. Passing the market price, and the risk that goes with it, down to the customers means that the RECs would no longer be the hedging companies, and that a large part of their profit mechanism would be removed. In a voluntary TOU or real-time-pricing scheme, customers could choose to use an REC heavily for hedging purposes and pay a flat rate, or choose to pay real-time, TOU or real-time capped rates with less hedging charges. In effect, we would be choosing which “insurance” policy to buy from the RECs, instead of being forced to buy the most conservative (and expensive) policy that gives us our flat-rate electricity price.

Most likely, RECs will resist such change, but that is a matter for the regulator Ofgem to rule on: the choice is between what is best for customers and network reliability vs. maximising the profits of the RECs.

4 Demand response analysis tool

In order to evaluate the potential effectiveness of demand response and embedded storage, a comprehensive software tool has been developed. The tool simulates disaggregated load profiles, bulk and embedded generation, embedded storage, real-time electricity forecasts, prices, and demand response scenarios. The remainder of this chapter will give a more detailed overview of how this tool works.

4.1 Overall model structure

A conceptual diagram of the model is shown here. Program flow is generally from top to bottom, while data flow is generally from left to right.

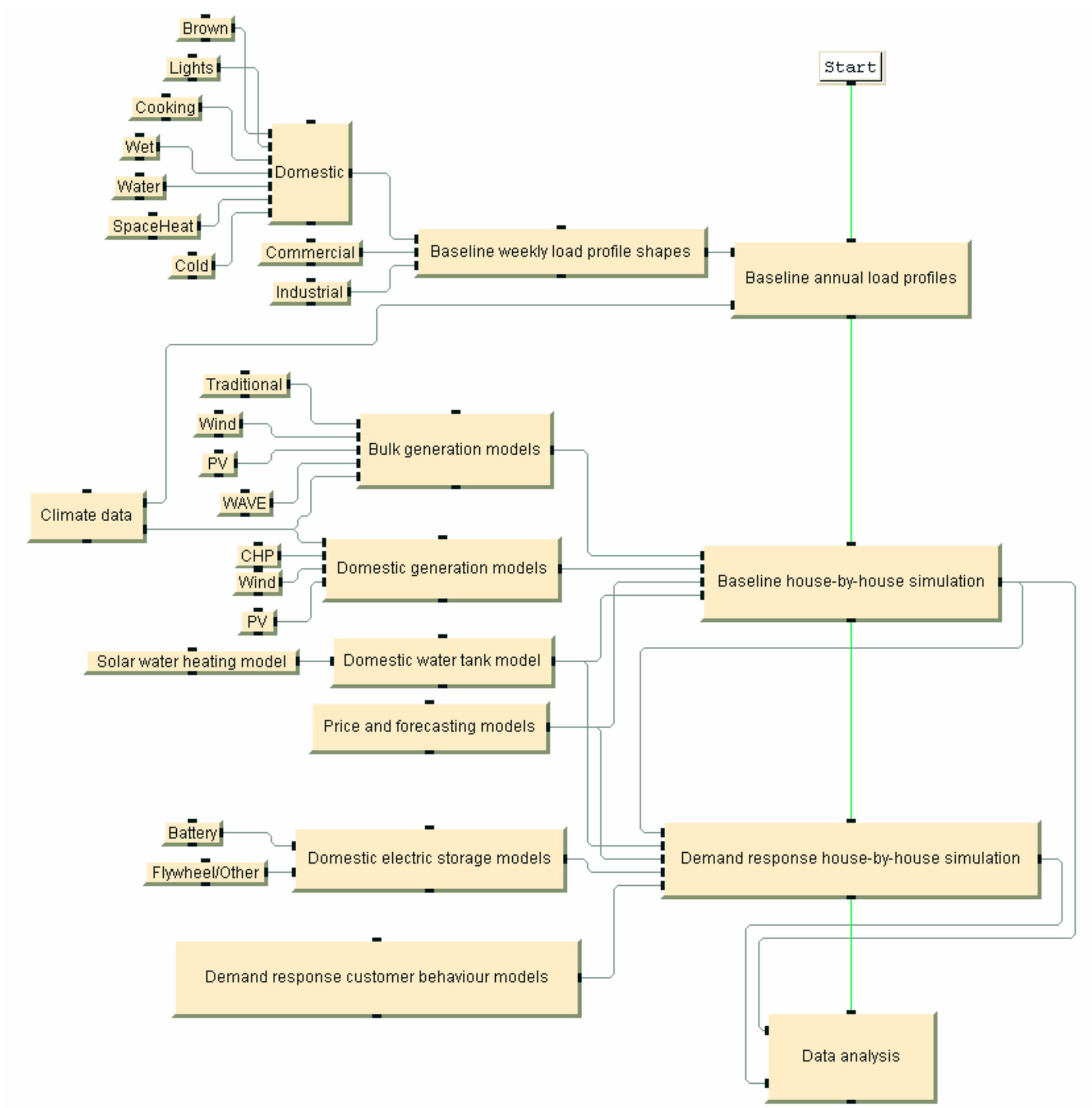


Figure 4-1 Demand response analysis tool: conceptual diagram

The actual flow diagram for the model is significantly more complex to allow for such things as partial simulations and the loading/saving of results. In particular, the results of the baseline simulations may be stored and re-loaded as the seed for many different demand response simulations. This allows a single baseline simulation to be taken as a "control", against which different scenarios of demand response can be compared.

The model is coded in a language called "Vee" which is published by Agilent Technologies. This language was chosen because it provides the following benefits:-

- An extremely rapid prototyping environment and debugging facilities
- Easy access to windows-based graphical output tools and data input widgets
- Array and matrix processing
- Familiarity of the author to the tool

In the following sections, the functionality within the major model blocks will be summarised.

The tool splits electrical demand profiles down into component parts, by load type. The profiles are simulated in time steps (nominally ½ hour long). The profiles are modified by climactic effects, and then applied to individual "houses" which can have different attributes of appliance ownership and behaviour. A baseline simulation produces a "control" result, and then a demand response simulation adds domestic storage and demand response actions. The results of the demand response simulation can be compared to the baseline simulation.

4.2 Correlation effects which are, and are not, modelled

It is useful to point out the factors which are NOT included in this modelling. Affluence and varying house sizes are not accounted for in the model. No account is taken of any correlations between affluence, house size and electrical demand. In the model, all houses are assumed to be of average size. No data was available providing any quantitative link between these factors, and it was not deemed appropriate to attempt to guess any such links. Likewise, no link is assumed between affluence and electric vs. gas heating/cooking ownership percentages, and no behavioural parameter depends upon anything other than a random number which is assigned to each house at the start of the analysis.

The model does make extensive use of climate-based correlations between renewable generation (wind, solar) and domestic heating demands (driven by temperature).

4.3 Baseline weekly 7-day load shapes

The overall electric demand profiles in this model are synthesised on a per-household average basis. The shapes of the sum profile for each house, on average, should end up looking like the shapes shown in Figure 2-8 to Figure 2-10. Simply taking the sum profile shape, however, would not enable the detailed analysis required in this report to be carried out. Instead, the individual components of the profile must be disaggregated from the sum. The model analyses the profile in the following parts

- Domestic brown appliances (TV, radio etc.).
- Domestic lighting
- Domestic cold appliances (Fridge etc.)
- Domestic wet appliances (Washing machine etc.)
- Domestic cooking
- Domestic water heating
- Domestic space heating
- Commercial (scaled to a per-household amount)
- Industrial (scaled to a per-household amount)

No data could be found in the public domain for the time-variant profiles of these component parts. Therefore, a best-guess approach was taken to the individual load profiles. For example, water heating requirements will probably peak around breakfast time and in the evenings, and TV usage will peak in the evenings. Weekend usage patterns for these types will probably be more spread out than weekday patterns. Cold appliance usage, on the other hand, is more-or-less constant over both 24-hour and 7-day timescales. Within the model itself, the basic 7-day profiles are built up by adding user-adjustable modified raised-cosine shapes. The raised-cosine waveforms are specified by:-

- Start time, T1
- Rise time, RF1
- Start weight, W1
- Fall time, RF2
- Stop time, T2
- Stop weight, W2

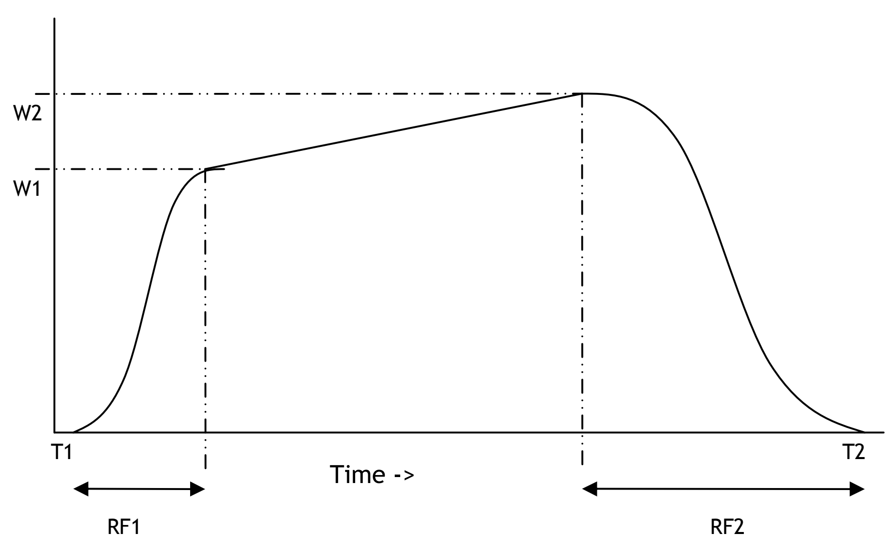


Figure 4-2 Load profile component

The load profile magnitudes are specified in relative weighting terms; it is not necessary to specifity the exact power magnitudes in Watts. The overall profile for each load type is built up by adding as many weighted raised-cosine shapes as required. The model allows for 3 separate weighted profiles for each load type:-

- A Monday-Friday profile
- A Saturday profile
- A Sunday profile

Shown below is an example of a seven-day profile; in this case for brown appliances (TV's, radios etc.) It can be seen that the Saturday and Sunday profiles (shown here as days=11-12 and days=12-13) have quite different load shapes to the Monday-Friday profiles.

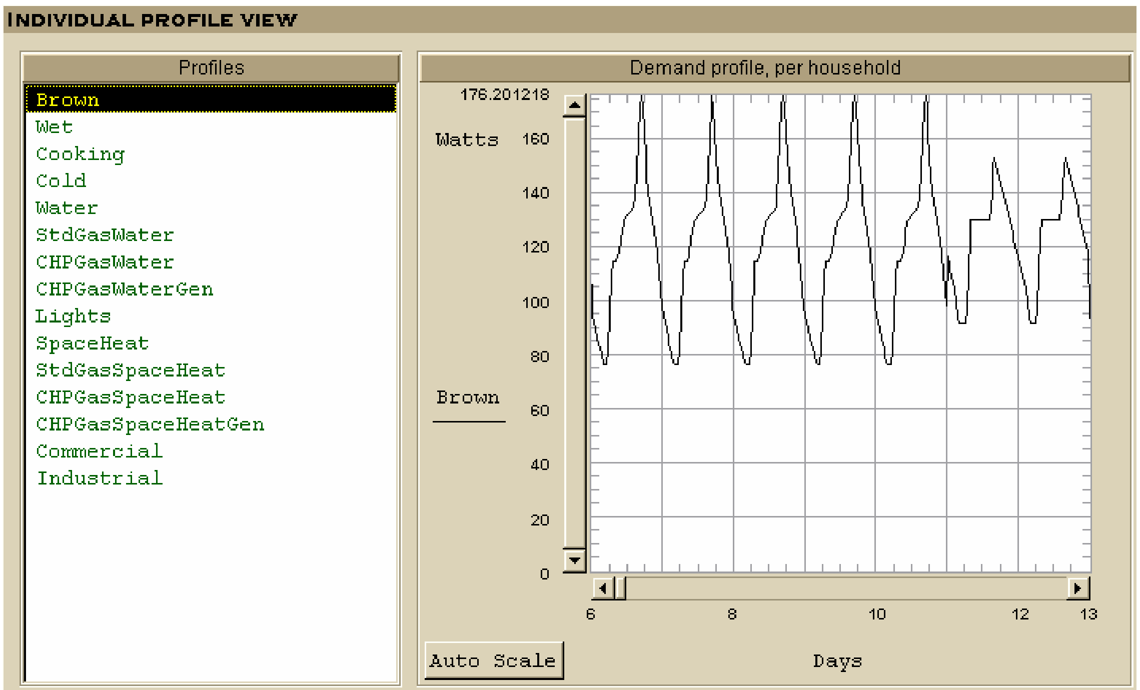


Figure 4-3 Basic weekly 7-day load profile for brown appliances, per household

The load profile shapes built up here correspond to human behaviour patterns and demands. At this point, the profiles do not account for climactic effects or seasonal load changing patterns. These are applied in the next stage of the modelling.

4.4 Baseline annual load profiles

Data is available from the DTI [8,10] giving a breakdown of annual electricity and gas use in the UK by appliance type. This data gives no indication of the profile of use against time-of-day, week or season. The figures are simply total use for each load type over a 12-month period. There are many different DTI tables from which the information summarised below has been collated into a useful format for this analysis. Even within the DTI figures for one year there are inconsistencies between tables. The figures presented below are believed to represent a fair picture of UK electricity and gas consumption in the UK for 2002/2003 after cross-correlating the figures between as many tables as possible. As well as plain electricity consumption, data for gas consumption and relative ownership rates for electric and gas appliances is gathered here. This enables scenarios of customer fuel switching between normal gas and CHP domestic boiler types, and gas to electric heating/cooking to be analysed.

	Lighting	Cold	Cooking	Brown	Wet	Space Heat	Water	Total		Commercial	Industrial
Elec Stats											
% Houses	100.0%	100.0%	60.0%	100.0%	100.0%	15.0%	15.0%				
TWh/annum (UK total)	17.99	17.15	10	26.9	12.8	23.2	13.8	121.8	TWh/a	98	111.75
kWh/house/day (ALL) avg	2.0	1.9	1.1	2.9	1.4	2.5	1.5	13.3	kWh/house/day	10.7	12.2
kWh/house/day (installed) avg	2.0	1.9	1.8	2.9	1.4	16.9	10.1	37.0	kWh/house/day		
Gas stats											
% Houses			40.0%			70.0%	70.0%				
TWh/annum (UK total)			8.1			272.9	98.2	379.2	TWh/a	101.3	176.6
kWh/house/day (ALL) avg			0.9			29.9	10.8	41.5	kWh/house/day	11.1	19.3
kWh/house/day (installed) avg			2.2			42.7	15.4	60.3	kWh/house/day		

UKHouses	25,017,000
TWh/annum to kWh/house/day	0.109514571
1 toe to MWh	11.63

Table 4-1 Annual UK electricity and gas consumption by load type

To create the actual annual load profile for each load type, the model takes the weighted profile shapes for each type, and then calculates the absolute power demands (in Watts per average household) against time by equating the total used energy over a 12-month period to the value of the numbers in Table 4-1. (Actually, in the model, the energy is equated over a 24-month period to TWICE the numbers in Table 4-1. This allows a smooth calendar of weekdays to be set up for an analysis over any period of the year including a crossing of the New-Year period). In the model, the numbers are of course configurable to allow changes. In particular, it is possible to adjust the ownership percentages for gas vs. electric heating and cooking. Since the model knows about both gas and electric consumption per average household, it can then adjust the electricity usages to simulate customer switching scenarios between gas and electricity.

For seasonally independent load types (i.e. Brown, Cold, Wet, Water, Cooking, Commercial and Industrial), the annual load profile per average household is now complete. For the load types Lighting and SpaceHeat, however, the profile power magnitudes vary in a more complex fashion with season (climate).

4.4.1 Lighting and space heat load profiles

Climate data for the model was taken from datasets at the University of Strathclyde. Specifically, the Dundee 1980 climate dataset sourced from the ESP-R package was used during the course of this modelling. The dataset contains temperature, wind and solar insolation data, sampled hourly over a one-year period. The climate data is loaded by the model, and then duplicated to form a seamless two-year period so that the 24-month energy usage may be calculated. (Again, we use a 24-month not 12-month period here so that a smooth calendar New-Year period is available for subsequent analysis).

The actual load profiles for Lights against time are adjusted according to the diffuse solar insolation from the climate data, and two additional factors which define lighting use:-

- DiffuseForMinLights (DFML) specifies the diffuse solar insolation level (in W/m^2) which, even when exceeded, causes only a minimal amount of lighting to be used. Below this level, however, the level of lighting used increases linearly to 100% when the diffuse solar insolation drops to 0. Nominally DFML is set to $100W/m^2$.
- MinLightsFactor (MLF) specifies the amount of lighting which remains on, irrespective of how high the diffuse solar insolation rises above DiffuseForMinLights. Nominally set to 0.2

These two factors modify the standard daily profile shape (as defined by the modified raised-cosine shapes). If the simple daily lighting profile shape at any time is denoted as P_t, then the actual real-time lighting profile L_t at time t can be expressed as

$$L_t = P_t\left(MLF + (1 - MLF)\left(1 - \frac{I_t}{DFML}\right)\right)$$

where I_t is the diffuse insolation at time t, clipped to a maximum of DiffuseForMinLights (DFML).

To calculate varying space heat loads against season and climate, the model takes account of both temperature and total solar insolation (diffuse plus direct solar) as they vary in time. The model takes account of the following factors which are user definable:-

- InsideTemp; the desired internal room temperature (nominally 20°C)
- SolarCollectorArea; the effective area over which a solar collection efficiency of 100% is assumed. This collected energy (due to total solar insolation) reduces the space heating power required. This attempts to model, in a very simplistic fashion, the reduction in space heating required on sunny days when radiation heats exterior walls or floods in through windows to directly heat internal rooms. Nominally, a figure of $4m^2$ per average household is used.
- TempInvariant; the amount of space heating which remains on at all times, regardless of climactic and seasonal variations. Nominally this is 0.2
- ThermalMassHalfLife; the half life (in days) of the internal building temperature as it varies dependent upon the external ambient temperature. A longer half-life corresponds to thicker walls with a larger heat capacity. Nominally, this is set to 1 day.

The first step towards calculating the space heat loads is to calculate the "degree-days-per-day" for each day of the 24-month period. The "degree-days-per-day" figure for each day takes into account the required "InsideTemp" figure, the average of the external ambient temperature over the 24-hour period, and also the averages of the ambient temperatures over 24-hour periods for the previous 15 days, with weighting factors applied in an exponentially decaying series as defined by the ThemalMassHalfLife factor.

Next, the daily energy influxes due to the total solar insolation are also calculated. Again, because the fabric of the building can absorb and store heat, the effective energy release on each day is calculated by using the weighting factors of each day and the previous 15 days solar collection, as defined by the ThemalMassHalfLife factor.

Calculating the actual electrical heating demands in Watts against time, in such a way that the overall annual (or in this case 24-monthly) energy equates to the numbers in Table 4-1, is not so easy in this case. The reason is that the energy balance equation for spaceheat depends upon both the "degree-days-per-day" figures and also the solar influx figures, in a non-linear fashion.

$E = \sum_i f\left(k.DD_i - SI_i\right)T_P$ where f(x)=x if x>0; 0 otherwise

Here E is total energy over the 24-month period (in Watt-hours), DD_i is the "degree-days-per-day" figure (after weighting) for each time step, SI_i is the energy release due to solar insolation in Watts (after weighting) at each timestep, and T_P is the number of hours in each timestep. k is a constant (in Watts per degree-day-per-day) which the analysis needs to find in order to balance the equation such that E becomes equal to twice the DTI figure for annual electrical space heat use. Due to the non-linear operation of f(x) (which does not allow a negative space-heating demand on any single day!), the equation cannot be solved directly for k. The model instead finds k via a Newton-Raphson iterative approximation. The amounts $f(kDD_i\text{-}SI_i)$ at each timestep i can then be calculated explicitly and these are the required average spaceheating electrical demands.

4.4.2 Spaceheat, Water and Cooking demands: electricity vs. gas

The model takes account of user-configurable percentage ownership figures of gas vs. electric appliances for space heating, water heating and cooking. From Table 4-1 it can be seen that ownership in 2002-2003 was approximately:-

- Space heating and water heating: Gas 60%, Electric 15%
- Cooking: Gas 40%, Electric 60%. These figures are a simplified figure based upon the actual consumption and ownership figures from DTI, since many houses currently have gas hobs but electric ovens.

In the baseline simulation that follows (see section 4.10), houses are assigned ownership of heating and cooking fuel types. The model assumes a direct link between space heating and water heating, since the figures for ownership are currently almost equal and common sense suggests that a gas boiler, once installed, will be used for both activities. Cooking ownership is assigned on a house-by-house basis independently of the space heating and water heating fuel type. Within the user-configurable energy use data provided to the model, the figures for current gas vs. electric appliance ownership and energy use are provided. Also, the desired ownership figures for the baseline simulation can be modified. This allows simulations to be carried out which analyse future cases of either increased or decreased gas ownership and corresponding changes to electrical ownership (gas-electrical fuel switching).

In the case of space heating and water heating demands, the model keeps track of not only electrical demand load profiles but also gas heating demand load profiles. This is important since the calculation of domestic CHP generation (see section 4.6) needs to know about gas usage profiles so that the boiler outputs can be determined. The model is also supplied with the efficiencies of both standard and CHP boiler types which it must account for in the calculations of both gas-electrical fuel switching and CHP generation. These efficiencies are nominally [23]:-

- Standard boiler gas->heat efficiency = 0.65
- CHP boiler gas->heat efficiency = 0.6
- CHP boiler gas->electricity efficiency = 0.2

The current (2002-2003) ownership level for CHP boilers is assumed to be 0%.

If electrical ownership of a certain “task” (eg cooking) is increased relative to the 2002-2003 (current) levels, the model assumes that electrical energy use for that task per new electrical customer increases by an amount equal to the displaced gas usage for that task, after accounting for gas boiler efficiency. Conversely, if electrical ownership is decreased relative to the 2002-2003 (current) levels, the model assumes that electrical energy use decreases proportionately to the current electrical energy use for that task. This is a small point, but an important technical detail, since it can be seen from Table 4-1 that current gas customers for space and water heating use much more energy than their electrical counterparts (16.9+10.1= 27kWh per house per day, on average, for a house using electric space and water heating, vs. 42.7+15.4=58kWh raw fuel gas use per house per day, on average, for a house using gas space and water heating).

4.4.3 Examples of baseline load profiles

The synthesised, disaggregated load profiles can now be presented by using some screenshots from the model.

This graph shows how the average per-household spaceheat demand varies over the full 24-month period which is used to equate the energy use to the DTI figures. The time axis spans a January 1st to January 1st to January 1st time period. Clearly the spaceheat demands are maximum during the winter months and minimum during the summer.

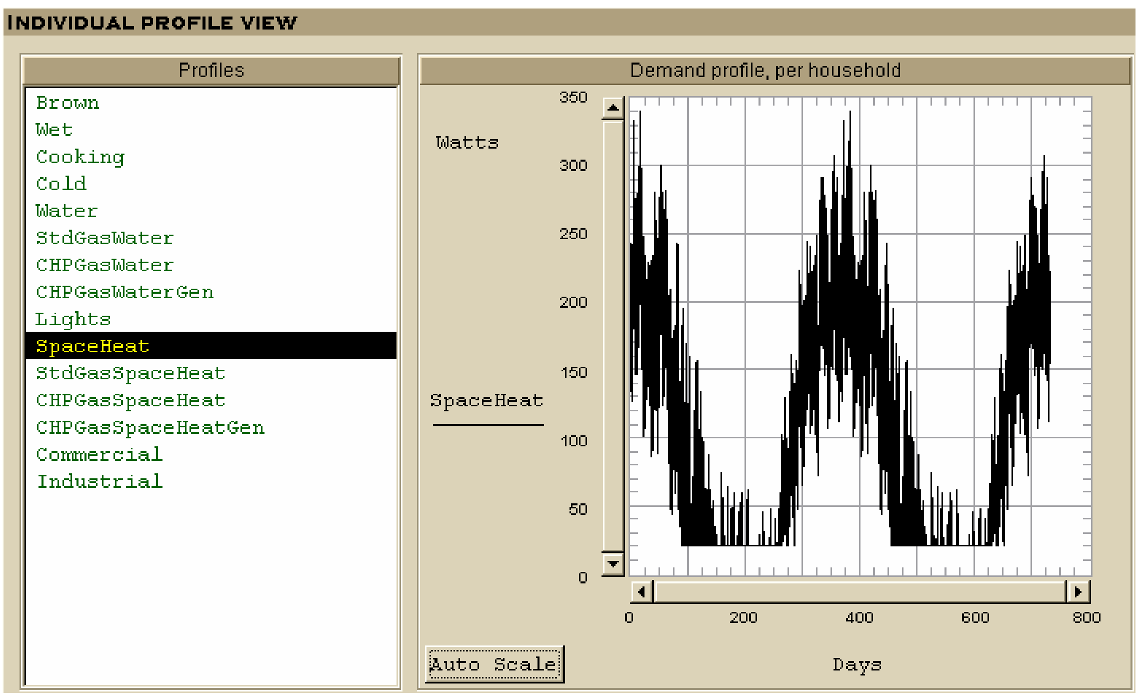


Figure 4-4 Electrical space heat demands per average house over 24 months (Jan 1-Jan 1)

It is important to remember that the demand figures (in Watts) here correspond to the average powers over all households. Since only 15% of houses currently use electric heating, the peak average figures here of 200W per household in winter relate to the full population of households, not just the households with electric heating. Therefore, within only those households with electric heating, the average winter demand is expected to be of the order of 200W/0.15=1.3kW over a 24 hour period.

This screenshot shows the spaceheat and lighting demands over a single week (Monday-Sunday) period in January. There is a drop in temperature to -6°C at day=3.5. which causes a peak in spaceheat demand on days=3-4. Lighting demand can be seen to drop when the diffuse solar component rises towards or above 100W/m^2. Note also that the overall shapes of both spaceheat and lighting demands are different between days 5-6 and 6-7, which are Saturday and Sunday respectively. Saturday and Sunday can have both different demand shapes and demand levels as defined by the modified raised-cosine definitions in section 4.3.

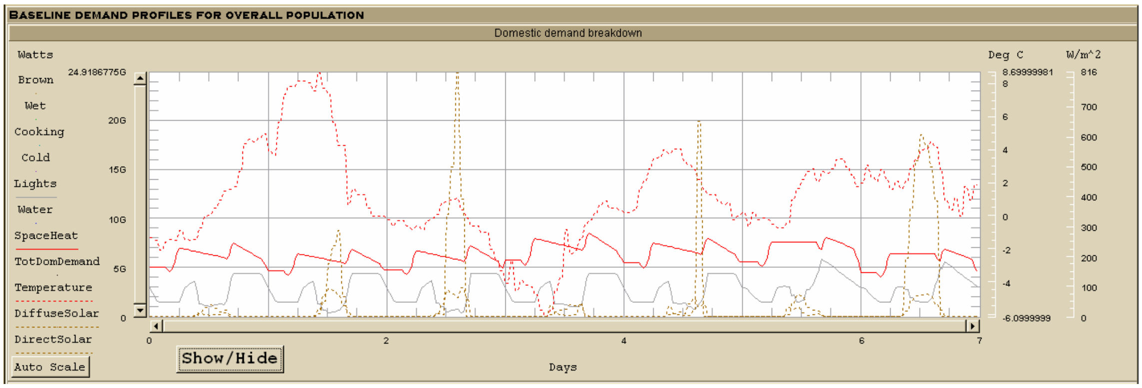


Figure 4-5 Electric space heat & light demands over one week in January (Monday-Sunday)

The demands here are scaled up by using number of UK households, which is approximately 25,000,000. This gives the overall UK domestic electricity demands for spaceheat and lighting during a week in winter.

This screenshot shows all the domestic load types, for one week in January. Again, the numbers are scaled for 25 million households to simulate a total UK demand.

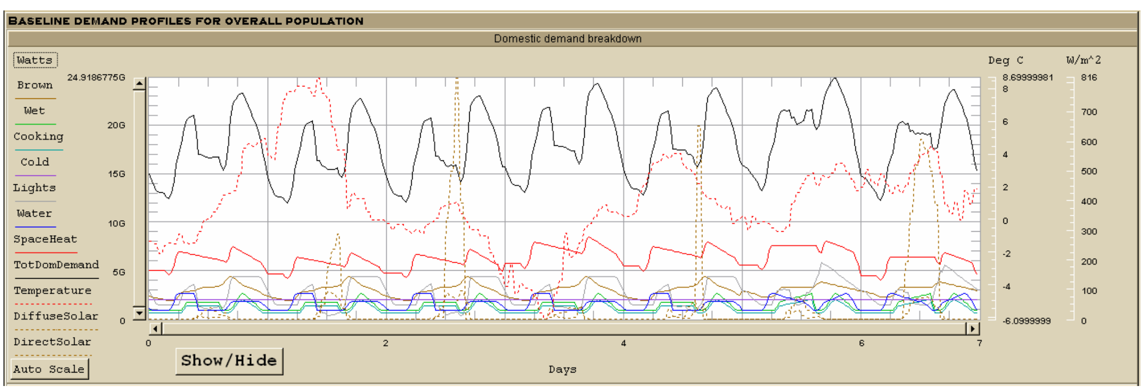


Figure 4-6 Domestic demands over one week in January (Monday-Sunday)

The key point to note from this graph is that in winter (when our peak loads occur), even with only a 15% figure for ownership of electric space heating, domestic UK electrical load is dominated by space heat demand. Any demand response program that is to be successful must bear this in mind. Space heating for many people in the UK will not be a luxury commodity, but a necessity. This situation is quite different from the "luxury" domestic air conditioning loads which were the target of several US incentive programmes to reduce electricity consumption.

Next, this graph shows the sum of domestic plus commercial plus industrial electricity use over the week in January. The total overall demand profile is not dissimilar to the actual known winter load profile shapes (for England and Wales) shown in figures Figure 2-8 and Figure 2-9.

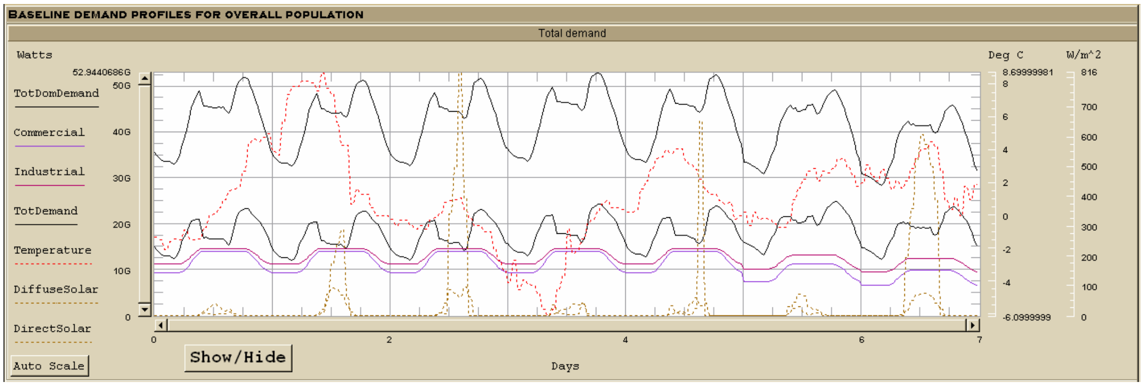


Figure 4-7 Total UK demand over one week in January (Monday-Sunday)

Below, the disaggregated domestic and total UK demand is presented over one week in summer. The domestic load shape is significantly modified (and lowered) since the spaceheat demands are much lower. The overall UK demand peak is lowered from 50-55GW to 40-45GW. The Summer demand peaks predicted here show a reasonable match to the real data shown in Figure 2-10, after accounting for the increase in households from the England&Wales data in Figure 2-10 (23 million households) to the UK data modelled here (25 million households)

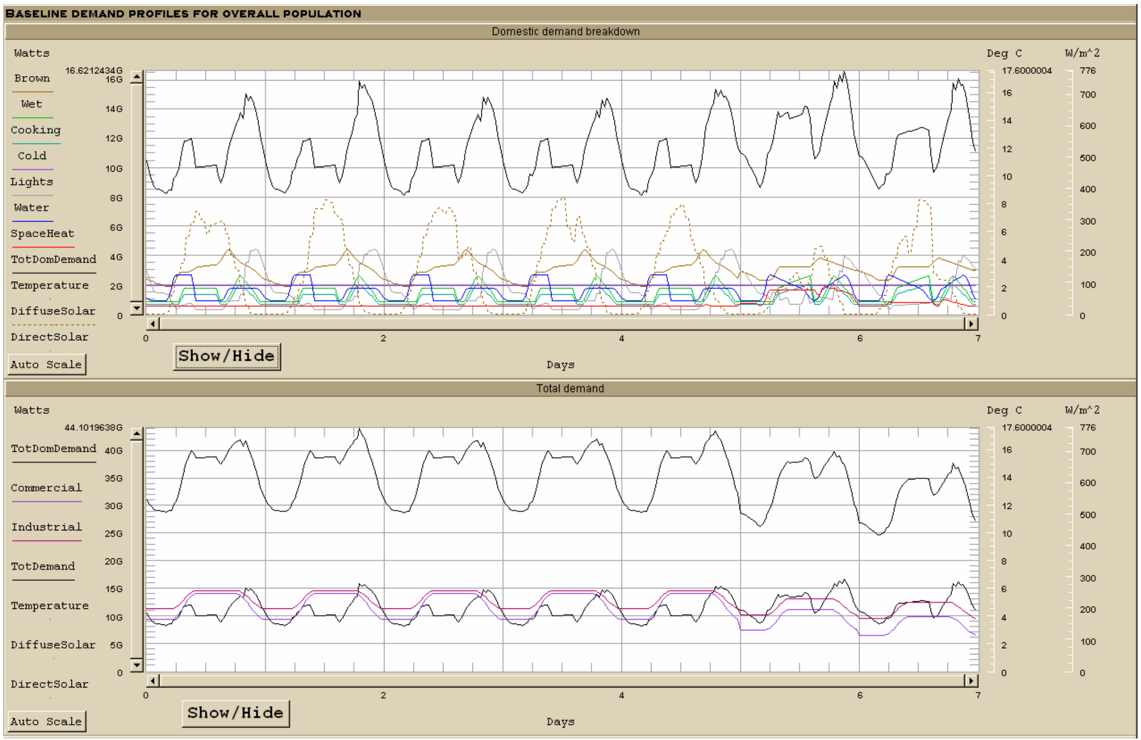


Figure 4-8 Total UK demand over one week in June (Monday-Sunday)

We conclude that although the disaggregated load profile shapes used here are unlikely to be 100% accurate (since they are composed by the author without any time-variant data from hard data), the profiles are generally of the right shape. The energy balance which is carried out guarantees that overall annual energy use for each load type fits known data from the DTI.

For the remainder of the baseline analysis, and for the demand response analysis presented in this report, it is not vitally important that the disaggregated demand shapes be 100% accurate, so long as they are reasonably representative of the real magnitudes and shapes of the demands. For any further analysis, if it was important to achieve greater accuracy in the disaggregated profiles, real data could be used to optimise the modified raised-cosine pieces so that the synthesised profiles more closely matched the real profiles. It is not clear where any real data to support this activity might be sourced from, however!

4.5 Bulk generation model

The bulk generation model is reasonably simple. Bulk generation may be supplied by one of the following types:-

- Traditional
- Wind
- PV
- Wave

The peak capacity of each generation type can be defined either as a fixed power in Watts, or as a fixed percentage of the overall calculated electrical demand peak which occurs during the simulation timescale (this will be determined during the baseline simulation). After the peak capacity has been set, the actual real-time capacities of each generation type are calculated over the simulation period by using the climate data.

Traditional generation is assumed to be available at all times on demand. The available capacity is a flat line against time.

Wind generation capacity is calculated by splitting the total wind peak capacity into installations. For example, 1GW of peak wind capacity, supplied by installations each of peak capacity (parameter PeakWattsEach) 100MW, implies that there are 10 installations. Each of these 10 installations is powered by wind. The wind data to each installation is modified from the standard climate data by:-

- A ClimateWindSpeedMultiplier (nominally 1) which allows the standard climate windspeed to be increased to simulate installations sited in favourably windy sites.
- A time shift offset in hours which is a random number between –HoursSpread and +HoursSpread. HoursSpread is nominally set to 24. This time shift allows a certain degree of de-correlation between the outputs of multiple wind farm sites. This simulates changeable conditions at different sites, and the effect of different wind directions on different sites. Prolonged periods of low windspeed will still cause correlated dips in available wind capacity, but brief fluctuations will tend to be flattened out. The smoothing effect will be greater if either HoursSpread or the number of installations is increased.

The wind power at each installation also depends upon the user-configurable parameters RatedWindSpeed, CutInWindSpeed and CutOutWindSpeed. These define the power output characteristics of the turbines.

PV generation capacity is also calculated by splitting the total PV peak capacity into installations. The solar insolation data to each installation is modified from the standard climate data by:-

- A time shift offset in hours which is a random number between –HoursSpread and +HoursSpread. HoursSpread is nominally set to 2. These time offsets create a smoothing effect identical to that described above for wind turbines.
- The available PV power at each installation also depends upon the user-configurable parameters RatedSolarWattsperm2 (nominally 1000) and Efficiency (nominally 0.15). These define the power output characteristics of the PV arrays.
- No account is taken of the angle of solar incidence – the bulk PV power stations are assumed to provide a scanning action which tracks the sun as it moves across the sky so that all available direct normal solar radiation is gathered.

The bulk wave generation model has only been created as a place keeper and is not complete. It has not been used during the analyses presented in this document.

4.6 Domestic electrical generation model (PV, wind, CHP)

The model allows simulation of several different modes of domestic electrical generation:-

- Domestic PV
- Domestic wind
- Domestic CHP from a boiler, driven by spaceheat and water demands

The domestic PV and domestic wind models simple re-use the same model from the bulk generation section (see section 4.5), although in this case the PV model simulates the fixed angles of domestic solar panels and the tracking action of the sun by using the vector mathematics derived in appendix 7.5. In the domestic case, the number of installations is defined by the number of households in the simulation, multiplied by user-configurable percentage ownership figures. The HoursSpread figures may also be modified, to simulate either widely dispersed or closely packed populations and the resulting correlation effects of climate-driven generation.

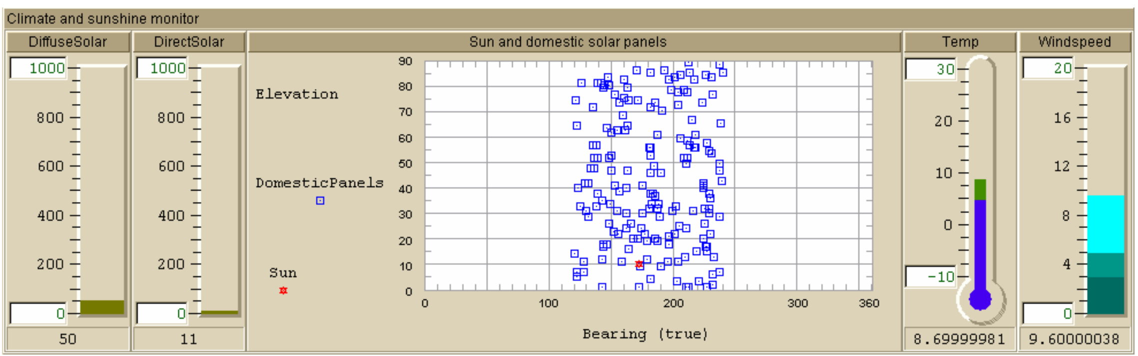


Figure 4-9 Example of climate, solar incidence angle and domestic solar panel orientations

To calculate domestic CHP generation, the model uses the demand profiles of space heating and water heating gas usage that are already known after the calculations described in section 4.4.2. The boiler efficiencies must be accounted for here, since the DTI annual usage figures for gas are expressed in raw fuel terms.

A simple example may be presented here, by regenerating the baseline profiles from Figure 4-5 to Figure 4-7 but for gas this time, and by assuming a hypothetical CHP (relative to total gas) ownership of 50%. The overall electrical ownership level for spaceheat and water is still set at 15%, and the ownership for gas spaceheat and water is still set at 70% (as per Table 4-1), but now 50% of the gas customers (ie 0.7*0.5=35% of all households) use a CHP boiler. For the same week period in January, the CHP generation across the UK amounts to a peak of 12GW. Notice that domestic electrical generation appears as a negative demand. Significantly, the peaks of CHP generation in the UK tend to fall at periods of peak electrical demand since space and water heating combined are such dominant parts of the domestic electrical load, even with only a 15% current electrical space and water heating ownership level.

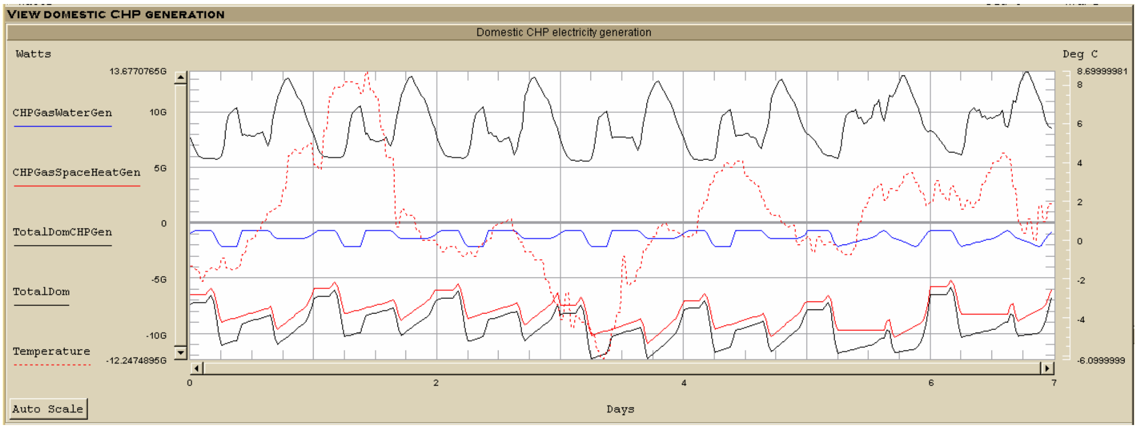


Figure 4-10 UK Domestic CHP generation & demand for one week in January (Mon-Suny)

The effect of this CHP generation on the overall UK demand shape in winter is shown below. Compared to Figure 4-7, the shape of the winter load profile is not much flatter in shape, but the absolute daily load cycling, measured from the peaks to the troughs, has been reduced from (53-32=21GW) to (42-26=16GW). The peak winter demand has also been reduced from 53GW to 42GW.

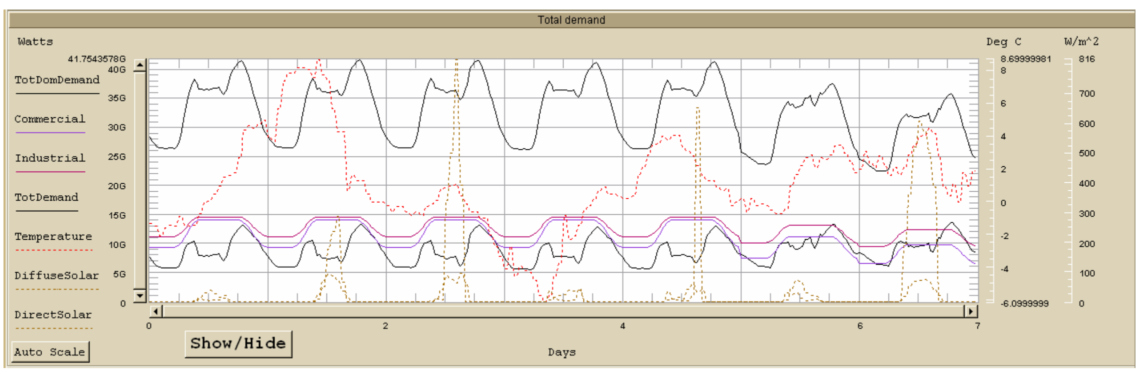


Figure 4-11 Total UK demand accounting for CHP over one week in January (Mon-Sun)

In summer, the space heating demands for both electricity and gas are much reduced. With the CHP generation added, the summer load profile over one week now looks as shown below.

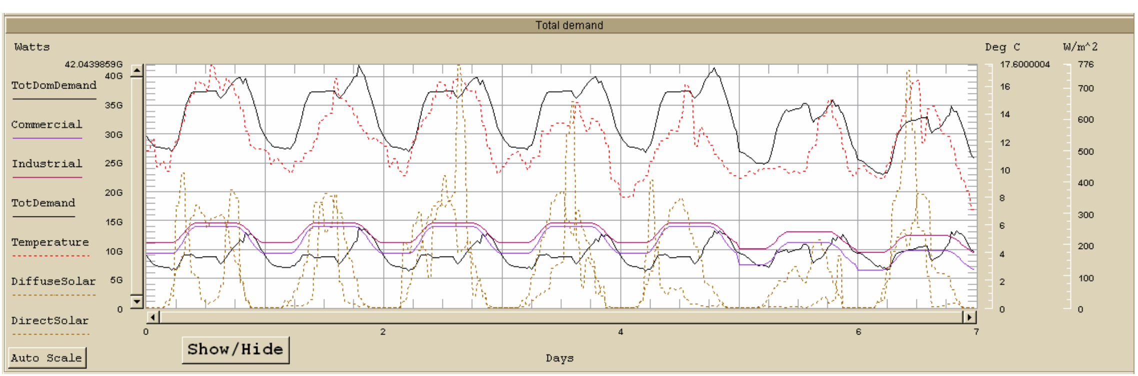


Figure 4-12 Total UK demand accounting for CHP over one week in June (Monday-Sunday)

The summer demand, accounting for CHP, looks similar to Figure 4-8 since the CHP generation due to space heating is relatively small.

The most significant point to note here is that with figures of approximately 70% gas space and water heating ownership and 50% of these houses possessing a CHP boiler, our UK winter and summer demand curves become very similar! Winter peak demands have been reduced to about 42GW, which is approximately the same as our peak summer demand. Analysis shows that increasing the level of CHP ownership from 50% to 75% means that UK summer peak demands would remain around 40-41GW while winter peak demands would drop further to about 37GW. Remember that the CHP ownership figure is a percentage of the overall gas space and water heating ownership, which is held at 70% for this analysis.

In conclusion for CHP, there will be a benefit for the annual "flatness" of electrical demand profiles in the UK as total CHP boiler ownership rises from 0% to 35% of all households (50% of 70%). Beyond this figure, the amount of CHP generation may be so large that it could reverse our summer and winter peak demand times. This would be a problem for high penetrations of renewables in the UK (particularly wind and wave) since our available wind and wave power will peak in the winter months due to the energy being dispersed in Atlantic depressions which is greatest in these same months. This effect of peak demand reversal from winter to summer could be offset, however, if ownership of electrical space heating was to rise from its current value of 15% (displacing some gas space heating ownership). This would cause increases in winter electrical demand. Ideally, a fair plan across the UK would be to encourage a gradual fuel-shift from gas to electricity (for security of supply reasons) while concurrently encouraging a gradual and balanced shift of remaining gas users to CHP systems.

4.7 Price model

The price model is a central part of this work; the way that price fluctuates with demand and supply will be the signal to customers that might persuade them to change their behaviour, or to invest in storage or efficiency measures.

The price model is based upon the analysis that was carried out in section 2.3.2. The data below is a review of this data, with low, middle and high estimates of bounding price curves super-imposed.

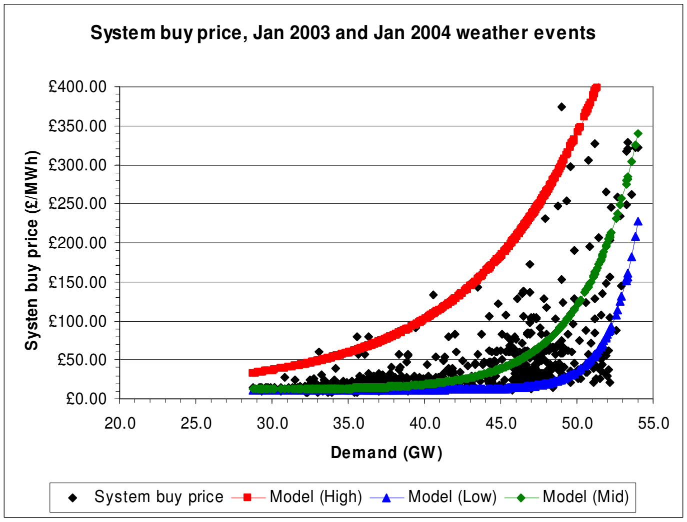


Figure 4-13 Wholesale price model candidate curves

The wholesale candidate curves are of the form

$\mathrm{Pr}\,ice = Ae^{Bx} + C$ where price is in £/MWh, and x is evaluated as

$$x = \frac{Demand}{Capacity - L\arg estGeneratorCapacity}$$

The values A, B and C for the three candidate curves here have been determined empirically, and are selectable within the model via a price model configuration screen. It is possible to select between the low, middle or high curves, or to specify an entirely different type of curve. Care must be taken to avoid mathematic errors in the price curve in the rare cases when demand becomes negative or exceeds capacity by a large amount. The price curves are all subject to an addition of a DUoS charge (nominally 8 £/MWh [19]) and then a price capping subsequent to evaluating the wholesale price equation. A figure of £500/MWh is nominally used for the price capping (50p/kWh). At the time of writing, the analysis does not account for different buy and sell prices to houses. This could be applied by subtracting 2xDUoS from the buy price. A house buying power at a flat rate of 7.5 p/kWh (including DUoS of 0.8 p/kWh, would expect to sell power at 7.5-2x0.8 = 5.9 p/kWh. This correction can only sensibly be applied to the overall domestic electric load which is the combination of all domestic loads and generators. Putting a revenue figure on domestic storage or generation then depends not only upon the amount of power imported, exported and generated, but also the times and relative weights with which these happen. Some generation will offset normal use and therefore form a benefit equal to the buy price, whereas excess generation will be exported at the sell price, incurring less revenue per kWh. Such a cost model needs care to set up, so that different load, generation and storage types are costed fairly. No attempt is made to do this in the current analysis. Only the buy price is considered.

The next picture shows the price curve configuration screen.

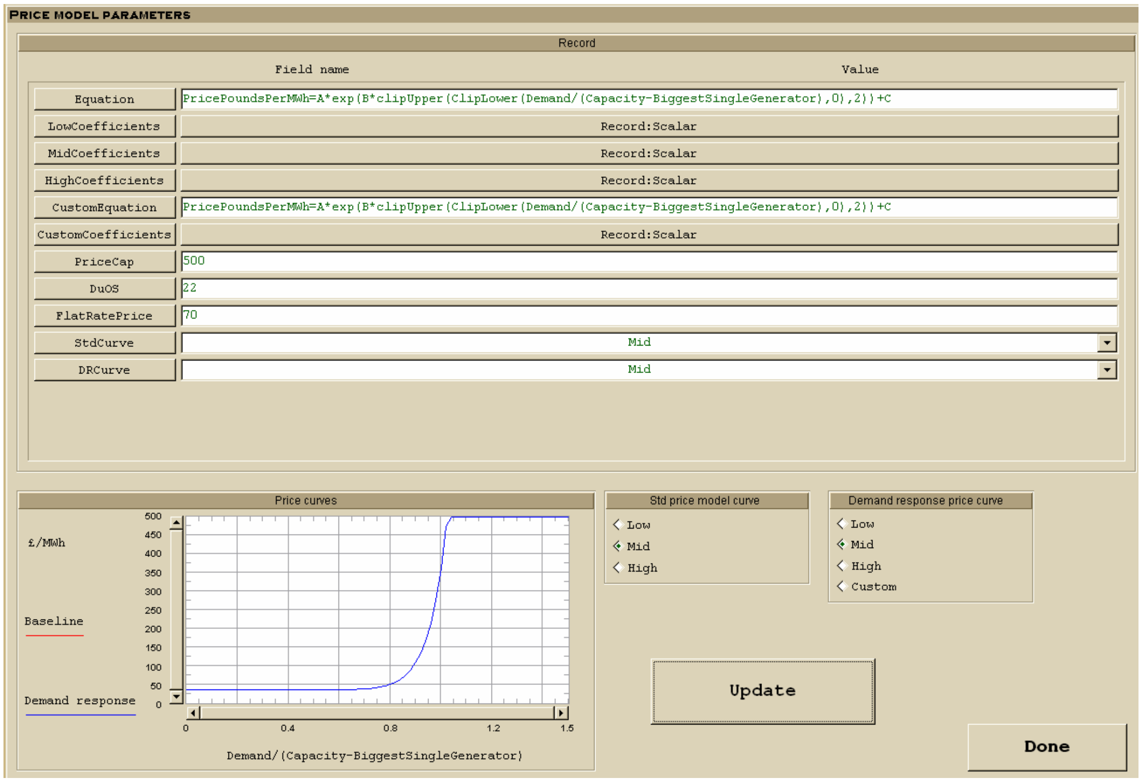


Figure 4-14 Price model configuration screen

The capacity of the largest generator, which is used in the price curve configuration, is a configurable parameter within the bulk generation model. The demand and bulk generation capacity are calculated during the modelling. Hence, at any time it is possible to evaluate the price of electricity in retrospect, subsequent to the completion of any time period, when the demand for a period has become a known quantity. However, this isn't much use.

To be useful, as a tool in a demand response scenario, the price must be forecast so that customers can be made aware in advance of impending supply shortages (expensive power) or supply excesses (cheap power).

4.8 Forecasting model and system stability

A good forecasting model is going to be a key component of any demand response program. In the simplest terms, what we require is a method of forecasting of the price of power, for time periods from ½ hour ahead to 24 hours ahead. This is a bare minimum; longer term forecasts (with less accuracy) of up to a week or two ahead would also be useful. In fact, rather than simply attempting to forecast price directly, what is required is forecasting mechanisms for supply capacity and demand loads. Once these two quantities are forecast, the forecast price can be simply evaluated from the two.

NETA are reasonably good at forecasting demand and supply in the UK, as described in section 2.3.2.1, for our current flat-rate inelastic system. It is not an easy task, however. Human behaviour, weather patterns, TV schedules, sporting events, power station outages and maintenance schedules are all things that must be taken into account in a decent forecasting algorithm. The situation becomes even more difficult when demand response and embedded storage becomes significant. Rather than forecasting something with a reasonably regular pattern, power demand profiles under a demand response scenario with embedded storage might vary wildly from the familiar shapes we saw in sections 2.3.2.2 and 4.4.3. Traditional forecasting tools that utilities currently use may well prove to be inadequate in this case. The forecasting tools will need to be adaptive, just as demand behaviour will be adapting to the electricity price.

In order to create a half decent forecasting model in a reasonable timeframe for this project, it was necessary to create an adaptive forecasting model that creates a forecast by simply looking back at past data and attempting to guess what the next data might look like. No attempt is made to account for any form of weather forecasting. Such an enhancement would be an interesting extension to this work.

The forecasting model looks back over a configurable number of days (nominally 15), and attempts to produce a forecast for a reasonable forward-looking timescale (nominally 24 hours). The forecasting model is used to analyse bulk generation capacity and overall demand. The price is then simply calculated from the two forecasts by using the price model.

The forecasting algorithm itself is based upon a first order polynomial fit (a linear regression) followed by a fourier analysis of the data. The details of this algorithm are well beyond the scope of this document but have been used previously by the author in several circumstances. The fourier technique is particularly suited to the forecasting of electrical demand since the demand tends to cycle over 24 hours and by week. The algorithm is fully adaptive – no assumptions are made about the shape of the capacity or demand profiles, the algorithm learns the shapes over several days and will adapt if the profiles change with time. This is a necessity since the demand profiles will change with time when demand response is significant.

It has been found that a slight tweak to the forecast figures in the short-term can make some of the forecasts more accurate.

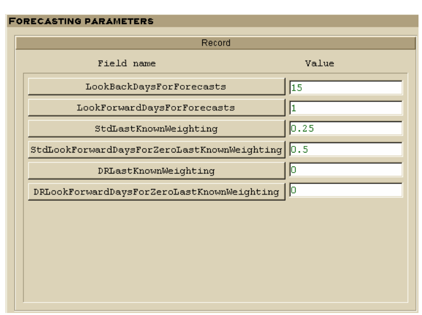


Figure 4-15 Forecasting model configuration screen

The parameters StdLastKnownWeighting and StdLookForwardDaysForZeroLastKnownWeighting define slight modifications which are made to all forecasts except the demand response forecast for electrical demand. Hence, these parameters are active for the baseline simulation forecasts for demand and bulk generation capacity, plus the demand response simulation forecast for bulk generation capacity. What these parameters mean is that the forecasting algorithm will compare (in retrospect) the forecast amount for the last period with the actual amount that occurred. The forecast for the next period will be modified by a factor of StdLastKnownWeighting times the actual-forecast error that was observed in the previous time period. The forecast for the next several timeperiods will be modified by linearly decreasing amounts until a time StdLookForwardDaysForZeroLastKnownWeighting days ahead, when the modification value drops to zero.

It has been found that applying this retrospective error modification to the demand response forecast for electrical demand can cause problems related with stability and oscillation, particularly when the price drives customer decisions involving electrical storage or immersion heaters.

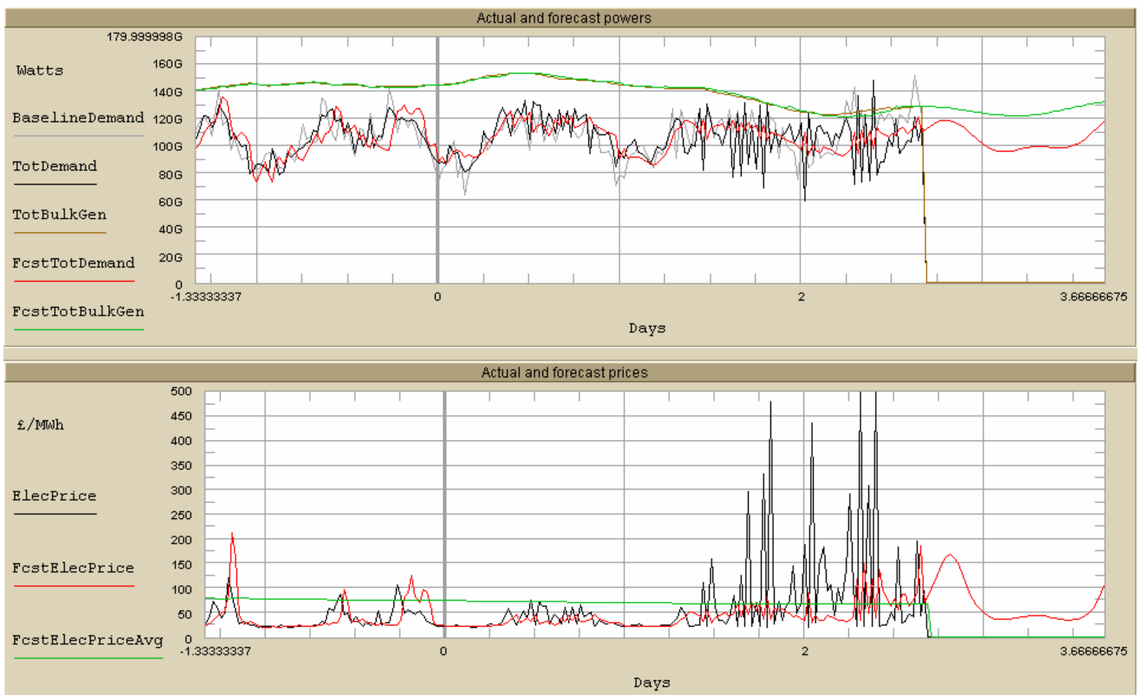


Figure 4-16 Example of demand forecast and price instability

The above screenshot shows an example of demand and price forecast instability. The instability begins at day=1.5, triggered by a sharp rise in demand to a point very close to the supply capacity. The demand and price forecasts begin oscillating out-of-phase with the actual electrical demand, while the relative price index forecast (price/average price) oscillates between less than 1 and more than 1. This oscillation in relative price index (RPI) causes houses to make buy and sell decisions en masse. The effect is devastating when RPI oscillates all the way from <0.5 to >1.5 since at this point every single household will make the same decisions. If RPI oscillates only from

0.8 to 1.4, say, then only a portion of the households will make the buy/sell decisions and feed the demand oscillations (see section 4.12.1).

This example was caused by a population with 100% penetration of immersion heaters which switched on and off in response to the price forecast. The immersion heater elements were 3500W each, which means that there is the potential for an 87GW shift in power demand if all 25 million UK households make the same decision at the same time. 60% of households also had battery storage with a 200W power capability, which adds another 1.5GW to the potential power swing. This behaviour, in combination with the steepening of the price-demand curves (Figure 4-13) as demand approaches supply, means that only small changes in forecast price can cause massive fluctuations in demand. Only a very robust forecasting algorithm in combination with diversity in population behaviour can avoid instability in this kind of scenario. In the case above (Figure 4-16), the forecasting algorithm managed to (temporarily) recover just before day 2, but in some cases the oscillation will only cease when demand drops well below capacity and the relative price index becomes s steadier value less than 1.

These are the reasons that the demand response forecast for electrical demand does not use the same parameters; it uses twin parameters DRLastKnownWeighting and DRLookForwardDaysForZeroLastKnownWeighting, which are nominally set to 0 so that the error modification is disabled. In addition, the stability of the demand response forecasts are enhanced (oscillation is reduced) by removing higher order harmonic products from the forecast. This equates to a low-pass filter in the time domain and is critical to reducing short-term oscillations in demand (and hence price) forecasts.

A theoretical analysis of system stability it presented in appendix 7.4, which assumes that a very simple forecasting model is used and shows that almost no storage power or immersion heater power can be controllable by price without instability. The forecasting algorithm used in this analysis is designed to avoid instability, so that larger storage powers and immersion heater elements may be controllable without instability. The algorithm is by no means perfect however, and development of better forecasting algorithms is a big area of future work.

The outputs of the forecasting model are (nominally) a 24-hour forecast of demand, bulk generation capacity, and hence price. This forecast is updated every time period (nominally every half hour) and forms a rolling set of data. Therefore, customers get an indication of future prices up to 24 hours ahead, but of course the forecast changes with time and there is no guarantee that the forecast will be accurate.

What is fixed, however, is that customers can only ethically get billed an amount for any time period based upon the forecast price which was issued a single time period ahead. The implication for not doing so is that the customer buys power at an unknown (and to them, random) price. So, at the beginning of each (half hourly) time period, the customer has a 24-hour forecast in half-hourly steps available. There is no guarantee that the forecast 24 hours or 2 hours ahead will be accurate, but the forecast price for the NEXT half hour must be the price that the customer actually gets billed for that half hour. This is the approach taken in this model, and is a minimum for social acceptability. In reality, to be socially acceptable, the forecast price for the next 2 or 3 (or more) hours might be the legal maximum price that the customer could be charged, no matter what actually happens to supply and demand over this timeframe.

4.9 Domestic water tank and solar water heating models

One of the main requirements of the model is to simulate domestic water tanks containing heated water. The hot water can be used to satisfy household needs for washing, bathing and for space heating via a central heating system. The hot water can also provide a useful store of energy if the tank is big enough and adequately insulated to efficiently store significant quantities of energy.

As described in section 4.4.2, the baseline simulation that follows models some houses with electric space and water heating, and others with gas heating. Only those houses with electric space and water heating are accounted for in the water tank model.

The model includes a simple design tool for water tanks. The user-configurable parameters are:-

- CapacityLitres: the maximum capacity of the tank
- HeightToDiameterRatio: nominally 2 for practicality, although 1 will lead to the lowest heat loss
- InsulationKValueWpermperK: nominally 0.04W/mK for expanded polystyrene or mineral wool quilt [23]
- InsulationThicknessMetres: nominally 0.01m for a standard tank, 0.05-0.1m for an efficient energy store
- TempUselessLowDegC: this is the temperature below which the water is useless to the user. Nominally 35°C
- TempMinDegC: the temperature which the immersion element will maintain when active
- TempMaxDegC: the maximum temperature which the tank may attain. This will be larger than TempMinDegC. TempMaxDegC is relevant when either a solar water heater is producing very hot water or when a demand response tank is buying cheap electricity to heat water and store energy. If this temperature is attained or exceeded, the immersion heater and solar water heater will deactivate until the temperature falls.
- LevelMinLitres: the minimum level of water that the tank may hold to avoid immersion element damage, and to satisfy user demands. This number can be as large as CapacityLitres, but setting it lower, for a large tank, can allow greater flexibility and efficiency in solar water heater capture energy.
- ElementWatts: the immersion element power, nominally 3000W

The model accounts for two types of tank. The first tank is a standard tank, of nominal size 120 litres which is a common size of immersion heater tank. The standard tank is used for all electric space and water heat customers in the baseline simulation. The second tank is a "demand response" tank which is designed to be bigger and with better insulation. The demand response tank is only used in the final "demand response" simulation, and then only by a configurable percentage of customers.

The model includes a simple design tool which processes the parameters for the two tanks and gives an indication of energy stored, heat loss, time to heat and time to cool. Part of this design tool involves solution of the differential equation governing temperature in the tank.

If:-

P = immersion element power consumption (Watts)

Q = heat lost through tank walls = $(T_w-T_a).H$ where T_w is the water temperature, T_A is the ambient temperature indoors which is taken to be the same InsideTemp as specified in section 4.4.1 . H is the heat transfer coefficient through the tank walls in W/K

then:-

$$\frac{dT_W}{dt} = \frac{P-Q}{mc_V}$$

solving this for T_W reveals:-

$$T_W = \frac{b}{c} + Ae^{-c(t-t_0)} \quad \text{where } b = \frac{P+HT_A}{mc_V} \quad \text{and } c = \frac{H}{mc_V}$$

A must be found by applying boundary conditions some start time T_0 with water temperature $T_{W0.}$

The solution can be re-expressed to find the time taken to reach certain temperatures as

$$t = t_0 + \frac{-\ln\left(\frac{T_W - \frac{b}{c}}{A}\right)}{c}$$

The statistics for two examples of tank are summarised below. The standard water tank (120 litres) stores between 4 and 8kWh of energy, dependent upon whether the reference energy is the water at the mains water temperature (nominally 6°C) or the minimum useful temperature of the water set by TempUselessLowDegC (nominally 35°C). The demand response tank stores between 18 and 32kWh. Note how the thicker insulation on the larger tank allows its heat loss power to be LESS than that of the smaller tank, despite having a larger surface area. The surface area of the tank will rise with the square root of the tank capacity, so increasing the insulation thickness by a factor of more than the square root of the capacity increase can lead to lower heat losses.

It might be argued that heat losses from the tank could count against space heating demands since the heat will be lost to the building interior (assuming the tank is indoors and the building sensibly designed!). This effect is not assumed or accounted for in the model. Providing good insulation on the tank will lead to a more controllable use and storage of energy and should be regarded as the "best practice".

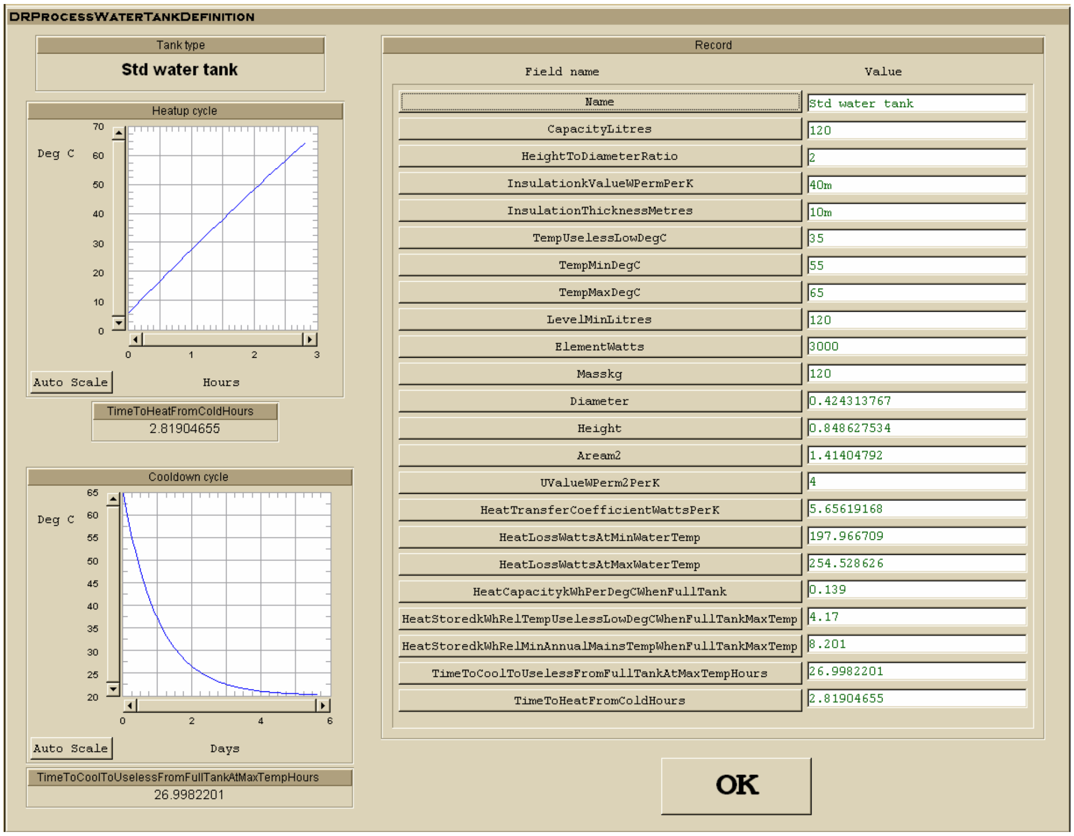


Figure 4-17 Demand response tank design tool output

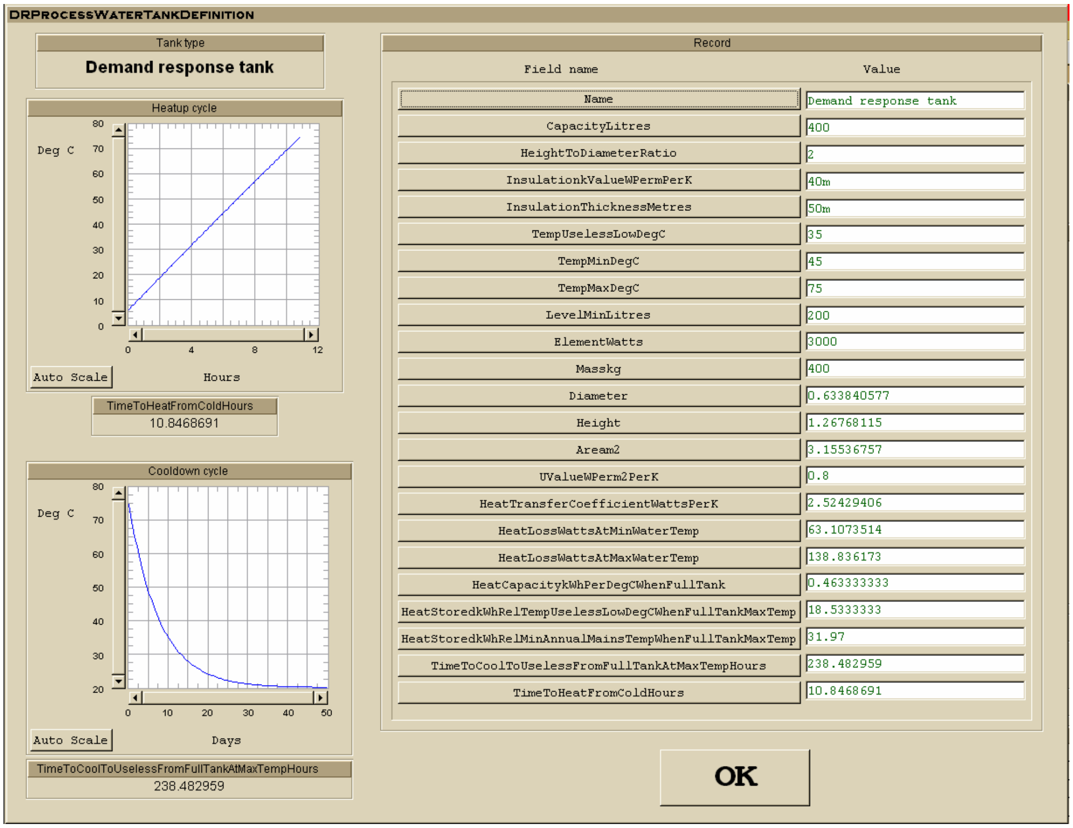


Figure 4-18 Demand response tank design tool output

The operation of the tanks is as follows, although small modifications are made if solar water heating is available and providing power (see section 4.9.3):-

4.9.1 Standard tank operation

Standard water tanks supply hot water for washing and bathing requirements etc. (i.e. NOT space heat demands which are provided by electric convection or radiation heaters).

- Hot water (and hence energy) is removed from the tank in each house according to the baseline water demand profile, multiplied by a reducing factor called StdWaterTankEnergyUsageEfficiency which is nominally 0.85. This figure modifies the electricity demand profile previously calculated into a water demand energy. The energy which has been “lost” is an approximation of the heat energy which is lost through the walls of standard water tanks. Put another way, although electrical water heat customers use 10.1kWh of electricity per day on average to heat water (according to figure Table 4-1), they actually only use, on average, about 10.1 x 0.85 = 8.6 kWh of hot water energy; the remaining 1.5 kWh is lost heat.
- The standard tank is always kept full to the LevelMinLitres level with water. For the standard tank, LevelMinLitres should be equal to CapacityLitres. The water to fill the tank

will come from the solar water heater (if available and providing power) or the mains water supply (nominally 6°C).

- It is assumed that users of standard tanks are good at predicting their hot water usage. Users turn on their water tanks (or program their immersion timers) in such a way that the immersion heaters come on to heat the tank of water to the TempMinDegC temperature just in time for use. This means the StdWaterTankEnergyUsageEfficiency parameter can be quite high, since the tanks often sit cool or cold when there is no water demand. With reasonably poor insulation (1cm) on a standard tank, heat loss at 55°C is about 200W, and the tank cools from 55°C to useless (35°C) in about 24 hours. The usage efficiency of such standard tanks would be much lower if the tanks were heated at times inappropriate for the demand for hot water. The model analyses water demand during the baseline simulation and switches on the immersion heaters in each house only when necessary.
- When the standard tank immersion heater is on, as required by the water tank demand, the heater element will heat the water up to the TempMinDegC level, and then the thermostat will turn the element off.

4.9.2 Demand response tank operation

The demand response (DR) tank is only used in the final “demand response” simulation, and then only by a configurable percentage of customers.

- DR water tanks supply hot water for washing and bathing requirements etc. PLUS space heat demands via a central heating system.
- Hot water (and hence energy) is removed from the tank due to hot water requirements in each house in the same way as for standard tanks.
- Hot water is removed from the DR tank due to space heat requirements, but this water is subsequently returned to the tank at a cooler (but still warm!) temperature because the central heating is a closed system. The flow rate and return temperature of the central heating water is determined by the tank water temperature, the building inside temperature, and a parameter called CentralHeatingHeatExchangerEffectiveness which is self explanatory.
- The DR tank must always be kept at or above the LevelMinLitres level with water, to avoid heater element damage. The water will come from the solar water heater (if available and providing power) or the mains water supply (nominally 6°C).
- The immersion heater element in the DR tank will always come on by thermostat if the water temperature falls below TempMinDegC. In this way, the aim is to always have on-hand a store of hot water to meet water and space heating demands.
- Finally, the immersion heater in the DR tank will switch on to buy power, regardless of the tank temperature relative to TempMinDegC, if the house is in a buy stance (see section 4.7). When this is occurring, the tank level will fill not only to the LevelMinLitres level but to a level which minimises the tank temperature so that heat loss is minimised.

The addition of water is limited by the tank capacity, and water will also not be added if the overall tank temperature would be dropped below TempMinDegC. The overall effect is that during times of low demand, when electricity prices are low, the DR tanks will tend to a) fill to capacity and b) get heated towards the maximum allowable temperature. The hope is that the stored energy can be used later, during times of potentially peak-price electricity, without being forced to purchase power at premium rates.

4.9.3 Solar water heating

Some houses can have solar water heaters installed. Only houses with electric water and space heating in combination with solar water heaters are modelled. The model includes a tool which helps in the design of the solar panels. A screenshot is shown here.

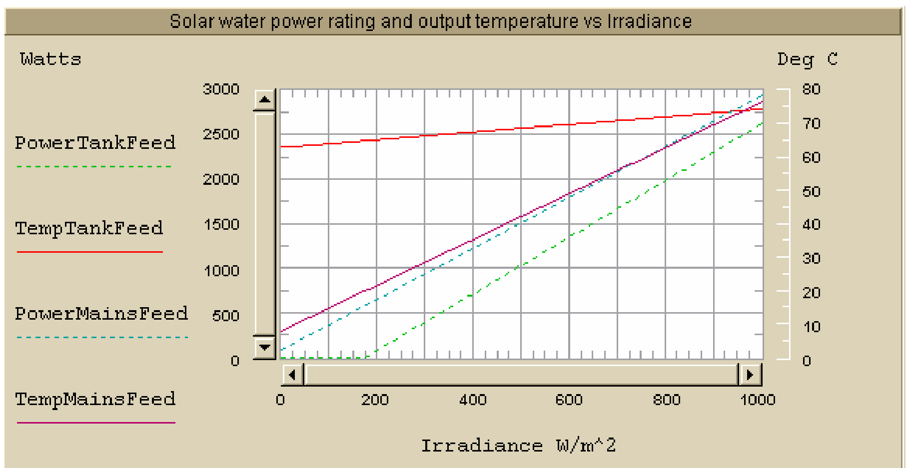


Figure 4-19 Solar water heater design tool

The solar water heater is designed using the following parameters:-

- Area (in m^2)
- Absorptivity, nominally 0.9 for black paint [23]
- UValue, nominally 2.8 W/m^2K for double glazing, low emissivity, 6mm gap [23]
- Transmissivity, nominally 0.9
- PumpRateLitresPerMinuteFromMains
- PumpRateLitresPerMinuteFromTank
- MinCutInTempDegC, nominally 10°C

The design tool allows optimisation of the pump rates. These must be set so that over a sensible range of solar irradiance from 200-1000 W/m^2, the resulting water temperatures from the solar water heater are hot enough to be useful, but not more than about 80°C. There are two modes of operation for the solar water heater.

1. If the water tank is filling with new water or the DR tank is not full to capacity, the solar water heater can heat water from the mains supply and add it to the tank if the temperature of the solar heated water is above MinCutInTempDegC.

2. If the water tank is already full to capacity, the solar water heater may operate if it can heat the warm tank water to a hotter temperature and return it to the tank with a net energy increase. For this mode to be successful, the heat loss through the solar panel double glazing must be less than the solar input power. In the example of figure Figure 4-19 this occurs only for irradiances greater than about $200W/m^2$.

The output temperature of the solar water heater is calculated by using the Hottel-Whillier equation:-

$$Q_S = GA\tau_C\alpha_P - [UA(T_C - T_A)]$$

where Q_S is the power supplied by the collector

G is the irradiance (total solar insolation), modified by the panel-sun pointing angle error as derived in appendix 7.5.

τ_C is the transmissivity

α_P is the absorptivity

T_C is the plate temperature

T_A is the ambient temperature (taken from the climate data).

Here, we estimate the plate temperature T_C to be the average of the feed water temperature to the heater T_{FW}(which is known) and T_S, the solar water heater output temperature. T_S is, however the quantity we wish to evaluate.

We can write

$$T_C = \frac{(T_{FW} + T_S)}{2}$$

and

$$T_S = T_{FW} + \frac{P}{\dot{m}c_V}$$

where c_V and $\dot{m}$ are the specific heat capacity and pump rate of the water.

Combining the above three equations eventually leads to this rather ugly equation for the solar water output temperature, without reverting to any iterative processes.

$$T_S = \frac{T_{FW} + \frac{A}{\dot{m}c_V}\left(G\tau_C\alpha_P - U\left(\frac{T_{FW}}{2} - T_A\right)\right)}{1 + \frac{AU}{2\dot{m}c_V}}$$

4.10 Baseline simulation

The baseline simulation models a population of households, by using the baseline average load profiles as a starting point. The following effects are included in the baseline simulation:-

- Bulk generation capacity due to traditional (controllable) generation plus renewables which are subject to climactic variations (the wind and PV models)
- Household use of the disaggregated load types, at current UK rates of usage
- Embedded generation due to domestic CHP, wind and PV
- Hot water use in electrically heated houses is calculated by using the standard water tank model (see section 4.9.1), in conjunction with the solar water heater model.
- Space heating in electrically heated houses is assumed to be supplied by convection, bar-radiation or fan heaters.
- Although customers in the baseline simulation are only billed at the flat rate price, the forecasting and pricing models are applied to the baseline simulation, so that the results may be compared to the subsequent demand response simulation.

The following effects are NOT included in the baseline simulation. These effects will be calculated in the demand response simulation:-

- Embedded storage as calculated by the domestic electric storage model
- Demand response (elasticity, load shifting and critical peak pricing)
- Allowance for customers switching to a demand response (DR) water tank which allows more efficient hot water storage and supplies not only hot water for washing but also for space heating.

To simulate the baseline situation, the user enters configurable parameters for

- The number of households N_H to be simulated (nominally 25 million, which is the number of households in the UK). 25,000 households would simulate a medium-sized town.
- The number of "simulation households" N_S. Ideally, this would be equal to the number of households. However, to avoid excessive computer resource use, this number should be limited to a maximum of 100's or 1000's.

The baseline simulation performs a time-series simulation of N_S houses, but during the data analysis stage at the end of the simulation, the sum electrical powers from all houses will be increased proportionately so that the presented total demand figures are those that would arise from a population of N_H houses.

N_H must be set large enough to create a smooth simulation, but not so large as to cause an excessive simulation time. As an indication, with an electrical heating ownership of nominally 15%, using N_H of 10 will only, on average, simulate 1-2 houses with electric heating and this will probably cause quite a "jumpy" simulation result. Therefore, N_H must be set as large as reasonably possible.

4.10.1 Assignment of house attributes

At the beginning of the baseline simulation, the N_H houses are assigned attributes at random, according to the ownership percentages defined by the user. There is no correlation between the attributes unless specifically mentioned below:-

- Does each house have electric cooking (Yes/No)?
- Does each house have electric water and space heating (Yes/No)?
- Does the house have a solar water heater in conjunction with electric heating (Yes/No)? This can only occur if the house has electric heating.
- Does the house use gas heat and water heating (Yes/No)? This can only occur if the house does NOT have electric water heating and space heating.
- Does the house have a CHP gas boiler (Yes/No)? This can only occur if the house has gas water heating and space heating.
- Does the house have wind generation (Yes/No)?
- Does the house have PV generation (Yes/No)?
- The "solar offset" of the house, measured in time periods (nominally ½hour each). The solar offset for each house is a random number between –HoursSpread and +HoursSpread as defined in the domestic PV generation model. The number is stored here because it is required for BOTH the domestic PV and domestic solar water heater models, and we assume correlation between the two models for each house in terms of insolation at any single point in time. The houses also have a "wind offset" which is calculated in the same way but this is only required temporarily for the domestic wind generation model, so the numbers are thrown away after use.
- The declination of domestic PV and solar water heater panels from overhead (flat)
- The azimuth angle of twist towards east of domestic PV and solar water heater panels

4.10.2 Quantisation of load-shiftable events

When demand response is to be applied later, some of the electrical load types are expected to be either inelastic or subject to elasticity only, as opposed to possible load shifting (see section 3.4.7.1). These non load-shifting load types are:-

- Brown
- Lights
- Cooking

Therefore, these load types do not need to be modelled on a house-by-house basis since each house simply takes on the average baseline load profile, to which elasticity can be applied in the demand response simulation. However, for the remaining load types:-

- Wet
- Cold
- Water heating
- Space heating

We require to model load shifting and water tank operation in the demand response simulation. Therefore, at this point in the baseline simulation, these load types are modelled on a house-by-house basis in a quantised form. This is done by using the average baseline load profiles as a probability density function and then assigning quantised event starts for each house individually by using Poisson distributions.

$P(k) = \frac{(np)^k e^{-np}}{k!}$ where P(k) is the probability of k events occurring at any time, and np is the average number of events expected at any time. The distribution has a mean of np and a variance of np also.

For each load type, there are user configurable parameters describing the nominal power and duration for a typical event. For example, the load type "cold" has a typical power of 150W and a duration of 0.5 hours. This simulates a fridge running on a duty cycle; we would expect it to come on in half-hour bursts and then be off for a while. Since average UK energy use for cold appliances is 1.9kWh/day, we expect 25 of these cycles per day, which equates to a duty cycle of about ½. For wet appliances, the nominal power is 2kW, with a duration of 1 hour, simulating a wash cycle. Since UK average figures for wet appliances are only 1.4kWh/day, we expect less than 1 cycle to appear per day, on average. The result is that for individual simulated houses, the wet, water and space heating load types will occur as demand spikes, while the cold load type will be more consistent on a fairly steady duty cycle. Only when many houses are simulated and the demands added will a smooth load curve be obtained.

Below is an example of a single household for two days in January, showing the quantised events for wet, cold, spaceheat and water demands. The cold events are at low powers but spread widely in time, whilst the wet events are rare. The wet events last an hour (two time periods) but have much higher power levels (2kW). The water demands are extremely spiky. These water demands are not actually electrical demands, they are converted to water tank heating demands by the standard water tank model (see section 4.9.1). The space heat demands are large and often, as this data is from winter. Remember, space heat demands in the baseline simulation are direct electrical demands since an electrical convection or radiation type heating is assumed.

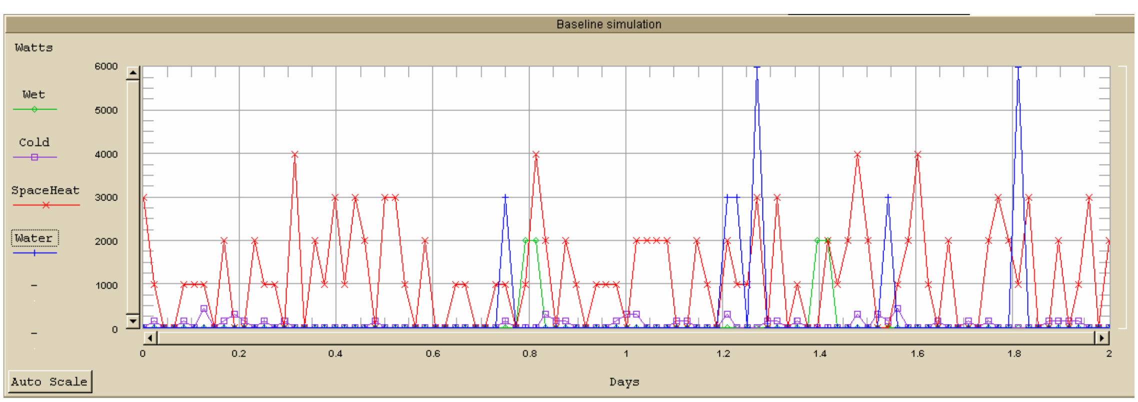


Figure 4-20 Example of quantised demand events in one house

To illustrate the action of the standard water tank model here, the following graph shows the water demand from above, plus the water tank heating demand. The tank heating power is capped to 3000W because this is the immersion heater element power. The tank heating occurs before the hot water is required, so that the tank is hot in time to fulfil the demand. This graph also shows the tank temperature and level for this house. The level is constant at 120 litres, but the temperature rises as the immersion element draws power and drops as hot water is taken.

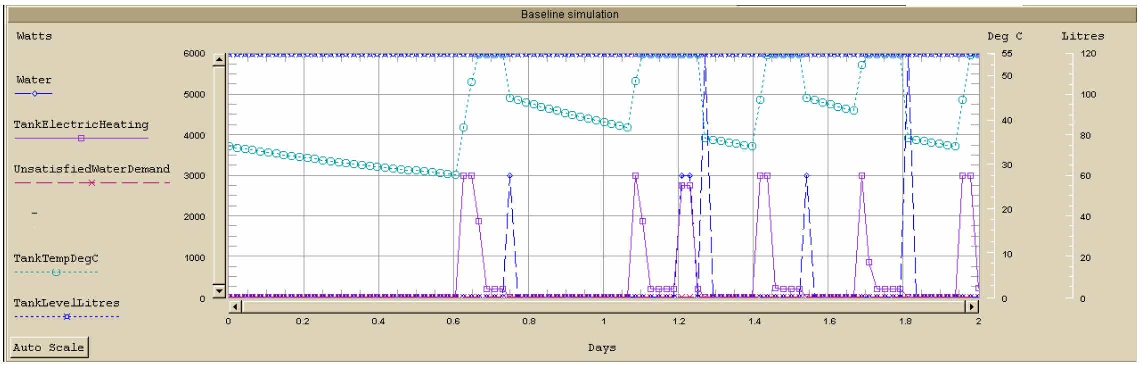


Figure 4-21 Example of quantised water tank demands in one house

The graph containing the sum power and average tank temperature of all N_S=100 simulation houses in this simulation, over the same 2-day period, looks as follows.

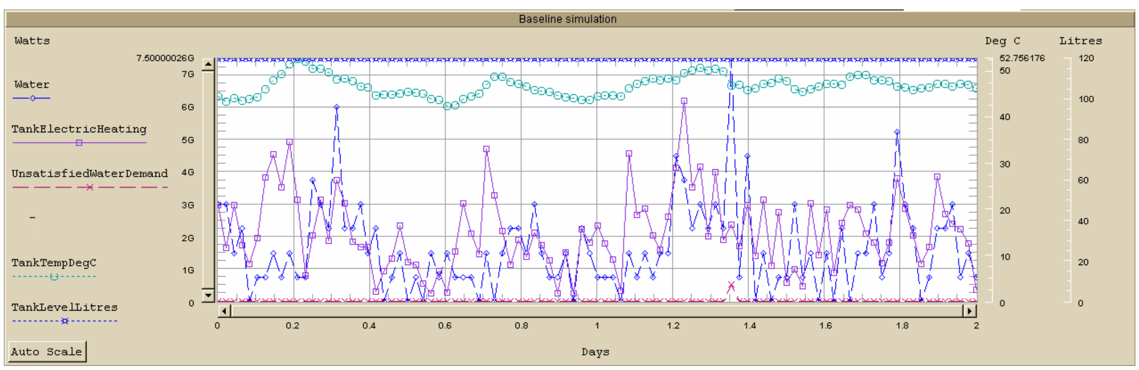


Figure 4-22 Example of quantised water tank demands, 100 simulation houses

Here we can begin to see peaks in hot water demand in the mornings (about day=0.25 and 0.75) and evenings (about day=1.25 and 1.75), although even N_S=100 simulation houses is not really enough to achieve a smooth curve with only a 15% electrical heating ownership since only about 15 simulation houses will contain these spiky quantised events. Here, the 100 simulation houses are representing 25 million households so the overall power levels are in the order of GW, since each of the 100 simulation houses represents 250,000 actual houses.

An interesting point to note on this graph is that at day=1.35 the parameter UnsatisfiedWaterDemand is not zero. This parameter is becomes non-zero when hot water demands become larger in any time period for any single household, than the available hot water in the tank. In real life this occurs when two or more people attempt to take a bath in quick succession, for example. The model will occasionally simulate these scenarios. They will occur more often if the tank size is not sufficient to meet demands. The UnsatisfiedWaterDemand parameter should be checked often to ensure that it does not exceed acceptable limits.

4.10.3 Running the baseline simulation

Once all the parameters have been set by the user, the baseline simulation simulates all the houses over the required simulation time period. As the simulation progresses, a real-time display of demand, capacity, actual price, and forecasts for all three is shown. This will be described in more detail as part of the demand response results in section 5.

4.11 Data analysis

The data analysis part of the model can be used to view the results of the baseline simulation, the demand response simulation, and make comparisons between the two. There is a huge quantity of data that may be presented, both graphical and in statistical format. To understand the outputs of the analysis, it is useful to describe the list of calculated parameters which may be explored. The parameter values all refer to data “sampled” at the end of each time step, apart from the forecast parameters which are calculated at the beginning of each time step. The first list contains parameters which are all powers, expressed in Watts:-

- Brown - the electrical demand due to brown appliances
- Wet - the electrical demand due to wet appliances
- Cooking - the electrical demand due to cooking (in those houses with electric cooking)
- Cold – the electrical demand due to cold appliances
- Lights – the electrical lighting demand
- SpaceHeatE – the electrical demand due to electric space heating from convection or radiation heaters
- TankElectricHeating – The electrical demand due to immersion heater element demands
- TotDomLoad – The sum total of domestic electrical demands (Brown+Wet+Cooking+Cold+Lights+SpaceHeatE+TankElectricHeating)
- *SpaceHeat* – the actual user demand for space heating. This can be fulfilled by either a direct SpaceHeatE electrical demand, OR, for houses with demand response (DR) tanks, a demand from the tank SpaceHeatW. Therefore, SpaceHeat=SpaceHeatE+SpaceHeatW
- *SpaceHeatW* - for houses with demand response (DR) tanks, a spaceheat demand which is taken from the tank via a closed central heating radiator system.
- Water – the actual user demand for hot water which is taken from the water tank.
- *WaterTankDemand* – the sum water tank demand power; WaterTankDemand=Water+SpaceHeatW
- *TankHeatLoss* – the power loss (heat) through the tank insulation
- *TankSolarHeating* – the tank heat gain due to successful operation of a solar water heater
- ***UnsatisfiedWaterDemand*** – any amounts of WaterTankDemand that cannot be met from the hot water the tank, because the water is too cold and/or the demand volume is more than can be supplied by the heater element working at full power.

- CHPGasSpaceHeatGen – the domestic generation due to gas space heating in houses equipped with CHP systems. (Generation appears as a negative power)
- CHPGasWaterGen – the domestic generation due to gas water heating in houses equipped with CHP systems. (Generation appears as a negative power)
- DomWindGen – domestic wind generation. (Generation appears as a negative power)
- DomPVGen - domestic PV generation. (Generation appears as a negative power)
- TotDomGen – total domestic generation. (Generation appears as a negative power). TotDomGen=CHPGasSpaceHeatGen+CHPGasWaterGen+DomWindGen+DomPVGen
- Battery – power flow into domestic battery storage
- Flywheel – power flow into domestic flywheel storage
- TotDomElecStorage – total domestic electric storage power flow. TotDomElecStorage=Battery+Flywheel
- TotDomDemand – total domestic electrical demand. TotDomDemand=TotDomLoad+TotDomGen+TotDomElecStorage
- Commercial – commercial electrical demand
- Industrial – industrial electrical demand
- TotDemand – total system demand. TotDemand=TotDomDemand+Commercial+Industrial
- BulkTradGen – bulk traditional generation capacity
- BulkWindGen – bulk wind generation capacity
- BulkPVGen – bulk PV generation capacity
- TotBulkGen – total bulk generation capacity. TotBulkGen=BulkTradGen+BulkWindGen+BulkPVGen
- **TotGenShortfall** – the generation capacity shortfall. TotGenShortfall=((TotDemand-TotBulkGen) clipped to 0 on the low side)
- FcstTotBulkGen – the forecast bulk generation capacity, at the beginning of the time step
- FcstTotDemand – the forecast total demand, , at the beginning of the time step ElasticDelta – the total demand change between the demand response simulation and the baseline simulation due to elasticity
- LoadShifting – the total demand change between the demand response simulation and the baseline simulation due to routine load shifting and critical peak price load shifting.

The parameters in italics (SpaceHeat, SpaceHeatW, WaterTankDemand, TankHeatLoss, TankSolarHeating and UnsatisfiedWaterDemand) are not true electrical demands but are measures of heat power flow.

The parameters in bold (UnsatisfiedWaterDemand and TotGenShortfall) are measures of system failure. When either of these two values is greater than zero, demand for hot water or electricity has not been fulfilled.

The remaining list of parameters are in units other than Watts. They appear as "correlation parameters" on the right hand axes of the graph sets:-

- ElecPrice – the actual effective price of electricity (£/MWh) (after addition of DuOS and price capping), calculated at the end of a time period when actual capacity and demand is known.
- FcstElecPrice – the forecast price of electricity (£/MWh) to the customer (after addition of DuOS and price capping), calculated at the beginning of each time period.
- FcstElecPriceAvg – the customers perceived average electricity price (£/MWh), calculated with a weighted average over a number of previous days.
- FcstRelPriceIndex – the relative price of the electricity for the next period. FcstRelPriceIndex= FcstElecPrice/ FcstElecPriceAvg
- FcstCriticalPeakSignal – a signal which is normally 0, but rises to 1 when FcstRelPriceIndex rises above some critical threshold (nominally 3)
- BuySellNeutralStance – a stance which is determined for each house at the beginning of each time period. Stance is -1 (sell) if FcstRelPriceIndex is >>1, 0 (neutral) if FcstRelPriceIndex is about 1, or 1 (buy) if FcstRelPriceIndex is <<1. (See section 4.12.1).
- Temperature in °C
- Windspeed in m/s
- DiffuseSolar insolation in W/m^2
- DirectSolar insolation in W/m^2
- TotalSolar insolation in W/m^2
- SolarWaterTempMains – the temperature of water (°C) at the outlet of the solar water heater, if it is fed from the mains supply (nominally 6°C).
- SolarWaterTempTank – the temperature of water (°C) at the outlet of the solar water heater, if it is fed from the tank.
- TankLevelLitres - the level of water in the water tank (litres)
- TankTempDegC – the temperature of water in the water tank (°C).
- TankEnergy – the stored energy in the tank (Wh), relative to the TankTempUseless parameter (nominally 35°C).
- BatteryEnergy – the stored energy in the battery (Wh)
- FlywheelEnergy – the stored energy in the flywheel (Wh)
- TotElecEnergy – (Wh) TotElecEnergy=BatteryEnergy+FlywheelEnergy
- TotEnergy – the total stored energy in embedded storage (Wh) TotEnergy=TotElecEnergy+TankEnergy

The data analysis tool allows statistics to be generated from the data for all the parameters above, correlated with the forecast, actual and flat-rate electricity prices. This allows calculation of the total electricity bills for each customer due to each load type. For the baseline simulation, the customer billed cost is calculated by using the flat rate electricity price (nominally 7.5p/kWh, £75/MWh). For the demand response simulation, the customer billed cost is the forecast cost, made at the beginning of each time period and communicated to the customer (see section 4.8) The load factors of the different load types can also be calculated, by LoadFactor=abs(MeanPower/PeakPower). To analyse electrical storage effectiveness and use, the actual mean power will be close to zero since power flow will be alternately positive (buying power) and negative (selling power). To allow for this, the mean "traded" power is also calculated; the traded power total being simply the sum of abs(power) over the period, and this gives a measure of the total power flow either bought or sold by the customer. The load factor for traded power is then abs(MeanTradedPower/PeakPower). High load factors close to 1 correspond to storage schemes in use often. If the storage scheme is to be effective, the revenue from the storage (measured by the negative billed cost of power) should be a large enough to cover the capital and operating costs of the storage.

4.12 Demand response model

The following effects, over and above the effects modelled in the baseline simulation, are added in the demand response simulation:-

- Embedded storage as calculated by the domestic electric storage model
- Demand response (elasticity, load shifting and critical peak pricing)
- Allowance for customers switching to a demand response (DR) water tank (see section 4.9.2) which allows more efficient hot water storage which supplies not only hot water for washing but also for space heat.

4.12.1 Pricing and its effect on customer behaviour in the model

The electrical pricing and forecast models were described in sections 4.7 and 4.8. In the demand response simulation, the forecast prices determine changes in customer behaviour. Specifically, each house is assigned a threshold for buying and selling power. This threshold is simplified in the model to a single number for each household, called "RelPriceIndexThresholdToBuyPowerLow". This figure is used, for each house, in each time period, to determine a "BuySellNeutralStance" which is either:-

- +1 if FcstRelPriceIndex < RelPriceIndexThresholdToBuyPowerLow, signifying that the electricity is expected to be cheap enough in the next period that the house would like to buy power into either electric or water tank storage.
- -1 if FcstRelPriceIndex > 1/RelPriceIndexThresholdToBuyPowerLow, signifying that the electricity is expensive enough in the next period that the house would like to either sell power from electrical storage, or at least to abstain from adding expensive energy to the hot water tank.
- 0, otherwise (a neutral stance).

The reader may like to refer back to section 4.11 for definitions of the pricing variable names used here. In particular, the FcstRelPriceIndex is determined by dividing the forecast electricity price by FcstElecPriceAvg, which is the customers perceived average electricity price (£/MWh), calculated with a weighted average over a number of previous days.

It will be shown later how important it is that the behaviour of the houses has a spread, caused by a spread in the values of RelPriceIndexThresholdToBuyPowerLow across the population. It is very important that the houses to not all make the buy/sell decisions at the same point in time, as this causes instability problems.

So, there are a number of parameters, forecast for the next time period and for the forecast-ahead period (nominally 24 hours), which can be used by each house to determine changes to its baseline electricity usage.

- The house has a forecast of the absolute and relative price of power
- The house has a forecast of it's "BuySellNeutralStance"
- The house has a forecast of FcstCriticalPeakSignal, the times when electricity prices are expected to be far in excess of normal due to generation shortfalls.

These forecasts are used by the house to determine actions in the electric storage, elasticity, load shifting and critical peak pricing models, according to some fairly basic rules.

Referring back to section 3.4.7.1 and applying common sense, some requirements for the demand response simulation modelling can be determined which will be suitable for the UK.

- For brown appliances, load shifting is not expected (it is unlikely people will watch a similar TV programme at *different* times due to price, they will simply not watch if it is too expensive, and they might leave TVs on more if it is cheaper). Brown appliances are modelled for elasticity only.
- For wet appliances, some elastic behaviour can be expected, so this must be able to be modelled. Also, it is quite feasible that a washing machine cycle could be shifted by some time (nominally 12 hours) to take advantage of cheaper power. Washing machines can also be delayed due to critical peak pricing.
- For cooking appliances, load shifting is not expected (people need to eat regularly!) but elasticity is valid since some small efficiency savings can probably be made.
- For cold appliances, we do not expect elasticity, since a fridge is either in use or not. Note here that in the long term (over years) fridge consumption can be elastic if device efficiencies gradually change, but this demand response model is not designed to model long-term elasticity dynamically. The long-term elasticity figures are embedded within the annual usage figures defined in Table 4-1. We do not expect active load shifting either, but we DO expect that fridges might be turned off temporarily (and hopefully only occasionally) due to critical peak price signals. In this case, we allow fridge cycle events to be delayed by only (nominally) 3 hours so that food is not spoilt.
- For lighting appliances, similar to brown appliances, we do not expect load shifting (people do not need to switch a bulb on later if they didn't earlier). We do expect

elasticity, however. In fact lighting is probably one of the most elastic load types in the UK. Remember, elasticity in this model is short-run elasticity due to hour-by-hour changes, not long-run elasticity. Long-run lighting elasticity can be caused, for example, by a shift to fluorescent bulbs, but this must be modelled by a change to the data in Table 4-1.

- For space heat, we allow the modelling of elasticity, load shifting and critical peak price load shifting. However, the aim is to be able to use the hot water tank storage reservoir in such a manner that hourly space heat demands are decoupled from electrical demands and the tank can be heated at times of cheap electricity. Therfore, the aim would be to assume a zero or very small elasticity and no load shifting.
- For water heating, the rationale is the same as for space heat, above.
- Commercial. Without detailed knowledge of individual premises, only a simple elasticity is assumed.
- Industrial, as for commercial.

4.12.2 Demand response house attributes

Houses are assigned attributes, in addition to the attributes already assigned in the baseline simulation 4.10.1. The attributes are allocated at random based upon percentage participation rates defined for the simulation. The additional attributes are:-

- RelPriceIndexThresholdToBuyPowerLow (a real number, nominally random between 0.5 and 0.95)
- Does each house have electric water and space heating (Yes/No)?
- Does each house use a demand response (DR) water tank in place of a standard tank in the demand response simulation (Yes/No)? This can only occur if the house has electric heating.
- Is the house actively load-shifting the wet appliance events (Yes/No)?
- Is the house actively avoiding critical peak prices for wet appliances (Yes/No)? This will always occur if the house is actively load-shifting the wet appliance events.
- Is the house actively avoiding critical peak prices for cold appliances (Yes/No)? Note, there is no active shifting of cold appliances.
- Is the house actively load-shifting the space heat appliance events (Yes/No)?
- Is the house actively avoiding critical peak prices for space heat appliances (Yes/No)? This will always occur if the house is actively load-shifting the space heat appliance events.
- Is the house actively load-shifting the water heat appliance events (Yes/No)?
- Is the house actively avoiding critical peak prices for water heat appliances (Yes/No)? This will always occur if the house is actively load-shifting the water heat appliance events.
- Does each house have electric battery storage (Yes/No)?
- Does each house have electric flywheel storage (Yes/No)?

4.13 Domestic electric storage model

For houses with electric storage, a simple model is used for both battery and flywheel types. Although the storage types are named battery and flywheel, other types of storage like superconductivity and hydrogen could almost certainly be modelled by re-using these models as long as suitable parameters were entered. Electricity is bought by a house if its BuySellNeutralStance is 1, i.e. the forecast electricity price is low enough to entice the house to buy electricity (see section 4.12.1). The amount of energy stored is capped by the storage capacity of the device. The amount of energy stored is also reduced, relative to the amount of purchased electricity, by the round-trip efficiency of the storage type. Further, the stored energy decays a little by a factor determined from a “half-life” parameter, every time period. The half-life for batteries and hydrogen storage is very long, but for flywheels is substantially less.

4.14 Elasticity model

The elasticity model is applied to each different load type at each time period. The actual electrical demand for each load type is determined by Equation 2 from section 2.3.1, by using the baseline demand and baseline flat rate electricity price (nominally 7.5p/kWh) as the reference quantities. The elasticities for each load type are defined at the beginning of the simulation from user input, and are expected to be either 0 for an inelastic load or an increasingly negative number for increasingly elastic loads. Remember from section 2.3.1 that elasticities between 0 and -1 correspond to commodities which are valued or necessities, whereas elasticities less than -1 are assigned to loads perceived as lower value commodities or luxuries. For smoothed power profiles (those not expected to be load shifted as per section 4.10.2), the calculation is fairly simple. For those power profiles expected to partake in load shifting, the electric demand events are quantised so cannot simply be increased or decreased by arbitrary percentages. In this case, the number of event starts for each load type at each time for each household is adjusted up or down by small amounts (using a Poisson distribution result as a modifier to the original Poisson distribution event starts), depending upon the elasticity equation.

4.15 Load shifting model

The load shifting model is substantially more complex than the elasticity model. The load types which allow load shifting were previously changed from smoothed power profiles to quantised events as described in section 4.10.2. For each of the shiftable load types (Wet, Cold, SpaceHeat and Water), the following algorithm is applied:-

- If energy is expensive and the house is in a sell stance (see section 4.12.1), and the load type is available for load shifting according to the house attributes (see section 4.12.2), then the customer will attempt to load-shift any current load event (e.g. washing machine cycle) into the future.
- The event cycles can only be shifted forward a certain maximum amount. For example, the default figure for wet appliances is 12 hours.

- The customer will attempt to move the event to the time with the cheapest forecast price in the available forward-shifting time window. If there is no cheaper time than the current, then the load will not be shifted.
- One the event has been shifted once, it may not be subsequently moved again, nor (in the model at time of writing) may any un-shifted events which already were due to happen at the new time that the event has been scheduled for. This rule applies no matter what happens to the energy price or the forecast. This model is not perfect but cleverer applications would be much more complex to implement and require much greater computer resource to track each event separately.

4.16 Critical peak pricing model

The critical peak pricing model is simply another application of the load-shifting model. This time, however, the threshold for each customer deciding to shift the load depends not upon the BuySellNeutralStance, but upon the relative price index RelPriceIndex (see section 4.12.1) and when it achieves a value greater than some defined constant (called RelPriceIndexThresholdCriticalPeakSignal and nominally 3). When this occurs, a critical peak price signal is assumed to be in effect. This could in reality be either communicated by the DNO/REC, or it could be determined independently in each household by the advanced meter. Each method has different advantages and disadvantages. In the simulation, the implementation is simplified in that all households are assumed to be paying the same price and averaging this over the same timeframe and therefore they all have the same perception of average price. Therefore, in the simulation, the critical peak price signal occurs for all households simultaneously.

An example of critical peak pricing and load shifting is shown below.

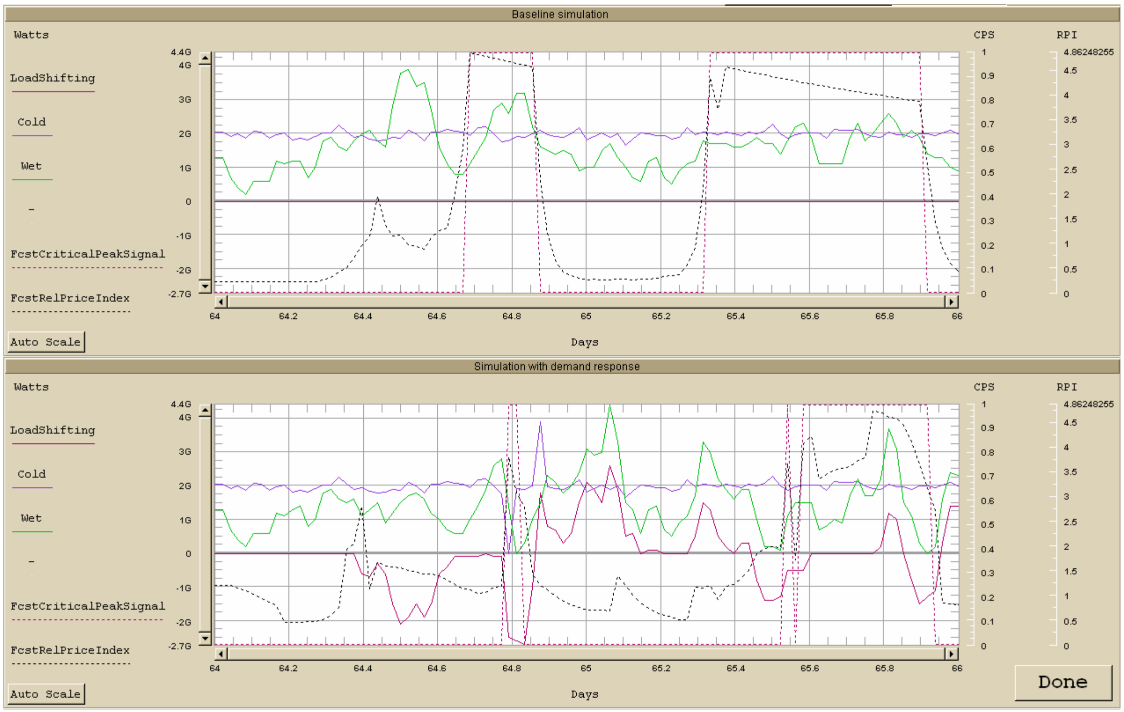


Figure 4-23 Example of load shifting and critical peak pricing

In this example, a critical peak price event occurs at day=64.8. At this time, all houses successfully managed to temporarily switch off their fridges (saving about 2GW from UK demand). The loads were shifted 2 hours (4 periods) into the future, when the critical peak price signal was expected to be removed. Also, a substantial amount of household load shifting occurred in wet appliances, shifting loads of the order of 2GW. The loads are shifted from periods of high price (here represented by the relative price index), to periods of forecast lower price. However, these shifted loads can cause their own demand spikes at the (supposedly cheaper!) later time, especially if all houses make similar decisions. Thus, load shifting can be effective at "peak clipping" and "valley filling" but can also lead to valleys becoming mountains if care is not taken!

Note that the cold events were not delayed due to the critical peak price signal at day=65.55. This is because the critical peak signal was forecast to remain in place, and shifting load from one critical peak to another serves no purpose.

4.17 Validation of the software model

Extensive validation of the model was carried out to ensure that energy and financial calculations were consistent. Each piece of the model, for example the water tank model, was tested individually after coding to ensure that energy was conserved and other inputs and outputs were consistent with the expected results given by manual calculations and estimations. As an overall test of the energy balance, a large simulation was carried out over a 365 day period. The overall energy usage of water tank immersion heaters and other load types was verified to be consistent with Table 4-1. The demand response simulation was verified to give identical results to the baseline simulation when all demand response parameters were set to neutral. The load shifting model was verified to give a zero overall energy gain/loss over the simulation period, save for a slight imbalance due to some events being shifted to beyond the end of the simulation period.

5 Analysis of demand response in the UK

In this chapter, simulations using the analysis tool (described in chapter 4) will be presented for a few interesting UK scenarios.

First, we present a summary of published data from several countries concerning likely elasticities of electrical loads, and attempt to use this to suggest sensible elasticities for an analysis of UK demand. Then, we present the result of a simulation representing a relatively near-term scenario for UK current energy use levels, assuming a reasonable dependence on wind power, along with a partial switch of gas users to CHP boiler systems.

Finally, we present a somewhat concerning simulation of the longer term future which assumes a complete fuel-switch from gas to electricity in the domestic, commercial and industrial sectors, without a general decrease in our energy use levels.

5.1 Indications of elasticity from published data

There are several studies which have been carried out around the world, in an attempt to quantify the elasticity of electrical demand. Some of these are theoretical and some are practical. A few are presented here.

- Filippini [17,18] presented two papers based upon a questionnaire data from 40 Swiss cities over 4 years which was then further mathematically modelled. The first paper estimates domestic short-run elasticity to be in the region of -0.6 to -0.8. In his second paper, after more complex mathematical analysis, he upped his estimates to -1.25 to -1.41 (peak electricity prices) and -2.30 to -2.57 (off-peak electricity prices). The significantly increase in elasticities between these two papers changed Filippini's view of electricity, particularly at off-peak times, from a necessity good to a luxury good since its elasticity was less than -1.
- DRAM (Caifornia [7]) present a concise review of elasticity estimates from 56 published papers. The results are shown below.

Summary Statistics for 56 Elasticity Analyses				
The Low and High Values Bracket the 95 Percent Confidence Band				
Geography	n	Short-Run Own-Price Elasticity		
		Low	Medium	High
California	13	-0.13	-0.21	-0.28
U.S.	36	-0.23	-0.28	-0.34
Other industrialized countries[2]	7	-0.28	-0.47	-0.66

Table 5-1 Summary statistics from 56 elasticity analyses

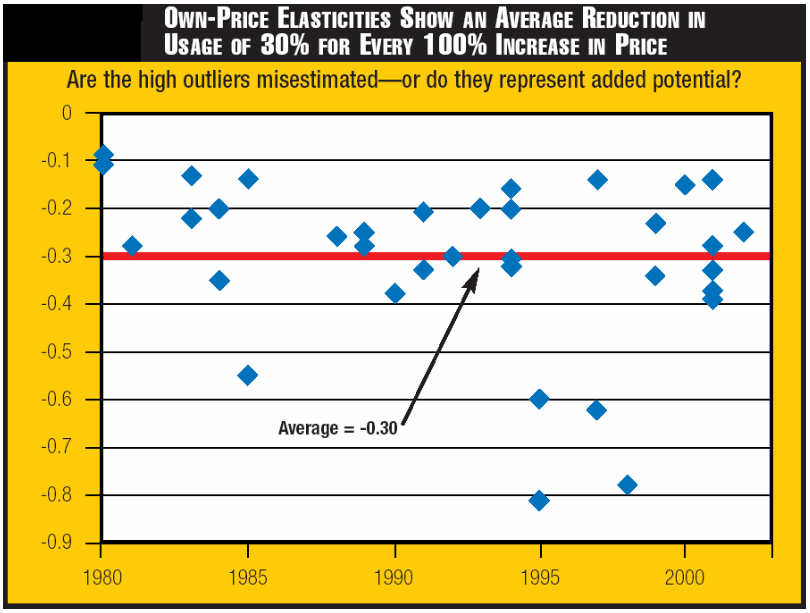


Figure 5-1 Summary statistics from 56 elasticity analyses

- Sheen et al [30] present data and analysis of large industrial customers in Taiwan, and they estimate own-price elasticity to be in the region of -0.75 to -1.8

There is considerable variation in all these presented results. Care must also be taken because not all the data will be applicable to UK scenarios since our peak demands occur during winter due to space heat demands whereas, for example, California peak demands occur in summer due to air conditioning. Also, many of the analyses above are concerned with TOU (time of use) schemes, where the own-price elasticities are only part of the story. Cross-price elasticities are equally important for many of the analyses published, since they model load shifting via elasticity models.

In the simulations to be presented here, elasticity figures are only used, as described in chapter 4, for loads which are either simply reduced or added due to the spot electricity price: any electrical demand which is not increased or decreased but instead deliberately moved to a time of cheaper price is modelled via the load-shifting and critical peak pricing models. So, to arrive at some suitable elasticities for the different load types, we must take all these effects into account and be a little conservative. We are attempting to split out simple overall electrical elasticity figures into own-price elasticities and load-shifting parameters for all our different load types. Here it is useful to refer back to section 4.12.1 which explains how the model works, and also section 2.3.1 for an explanation and table showing the elasticity effect.

- For brown appliances, we can expect quite a high elasticity, as they are a luxury good. Estimate -0.5
- For wet appliances, we can expect only a low elasticity (estimate -0.1), but there will also be load shifting.
- For cooking, we expect a relatively low elasticity (estimate -0.1)
- For cold appliances, there is no elasticity, since the fridges are always on.

- For lighting appliances, we can expect quite a high elasticity as people are currently very bad at leaving lights on. Estimate -0.5
- For space heating and water heating, we expect a low elasticity (estimate -0.1), but hope that storage will smooth out the demand peaks.
- For industrial and commercial demands, we assume here an elasticity of 0, to restrict our analysis to the domestic sector.

All these figures are value-judgements made by the author on the basis of gathered material, common sense, and the elasticity behaviour shown in Table 2-5. Note also that in these simulations we will be modelling short-run elasticity effects only. We are assuming that overall energy consumption drivers remain about the same. Some papers refer to long-run elasticities, but these account for customers being able to purchase more efficient devices or install extra building insulation. These effects are outside the scope of this thesis, but can be accounted for in the analysis tool by altering the overall energy use figures at the beginning of the simulation.

5.2 Demand response simulation 1 – near term analysis

The first simulation is a near-term simulation. There are many input parameters, many of which are left at the nominal figures described earlier in this text and are not described explicitly here. The main properties of this simulation are:-

- Overall energy use demand is assumed the same as current rates
- Electrical water and space heating ownership is 15% (2003 level)
- Gas water and space heating ownership is 70% (2003 level), but 50% of these people are assumed to have switched to a CHP boiler. Therefore, MORE gas will be used than 2003 levels, since the gas will be used to both heat and supply electric power. The CHP boilers supply domestic electricity, often (usefully!) synchronised with times of peak electrical demand as described in section 4.6.
- Electric cooking ownership is 60% and gas cooking is 40% (2003 levels)
- A 30% uptake of domestic PV (600W pk, $4m^2$)
- A 30% uptake of domestic solar water heaters within the 15% of electrically heated houses ($4m^2$, 2.5kW pk)
- 100% of people respond to critical peak price signals with cold and wet appliances, and that 75% of people actively load-shift with their wet appliances.
- Elasticity figures as described in section 5.1.
- There are 25,000,000 households, which we simulate with 500 houses so that there are a decent (500*15%=75) number of simulated electrically heated houses.
- Only 35GW (peak) of traditional bulk generation, and 30GW (peak) of wind generation capacity.

The simulations run over an identical time periods of three months (93 days), during the winter period. Over the time, the temperature, solar insolation and windspeed data is shown below.

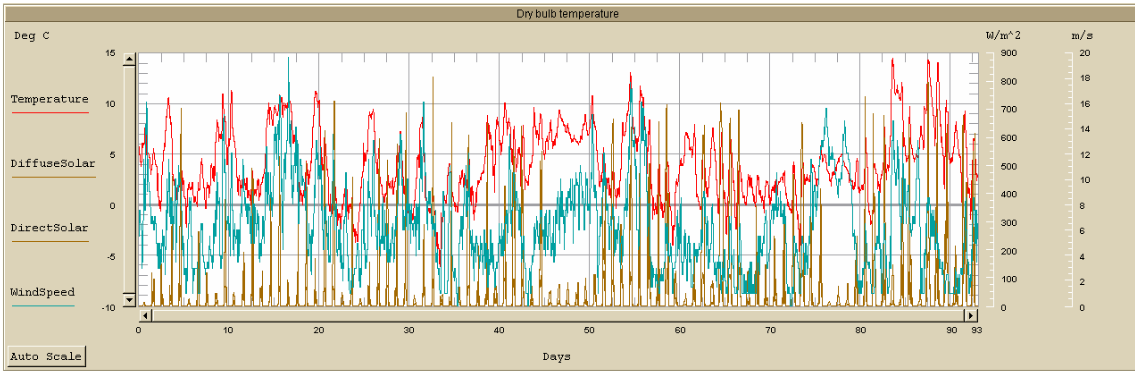


Figure 5-2 Climate data over the three-month (winter) simulation period

It can be seen that there may be several problem areas within the timescale, where either temperature or wind-speed drops for a number of days consecutively. These will cause demand increases and generation decreases respectively. Solar water and PV generation will be minimal on days without significant direct solar radiation.

5.2.1 Simulation 1 results

An overview of simulation 1 is shown below. The baseline simulation (without demand response, at a flat rate of 7.5p/kWh), is shown at the top. The lower graph set is the situation when real-time pricing is introduced.

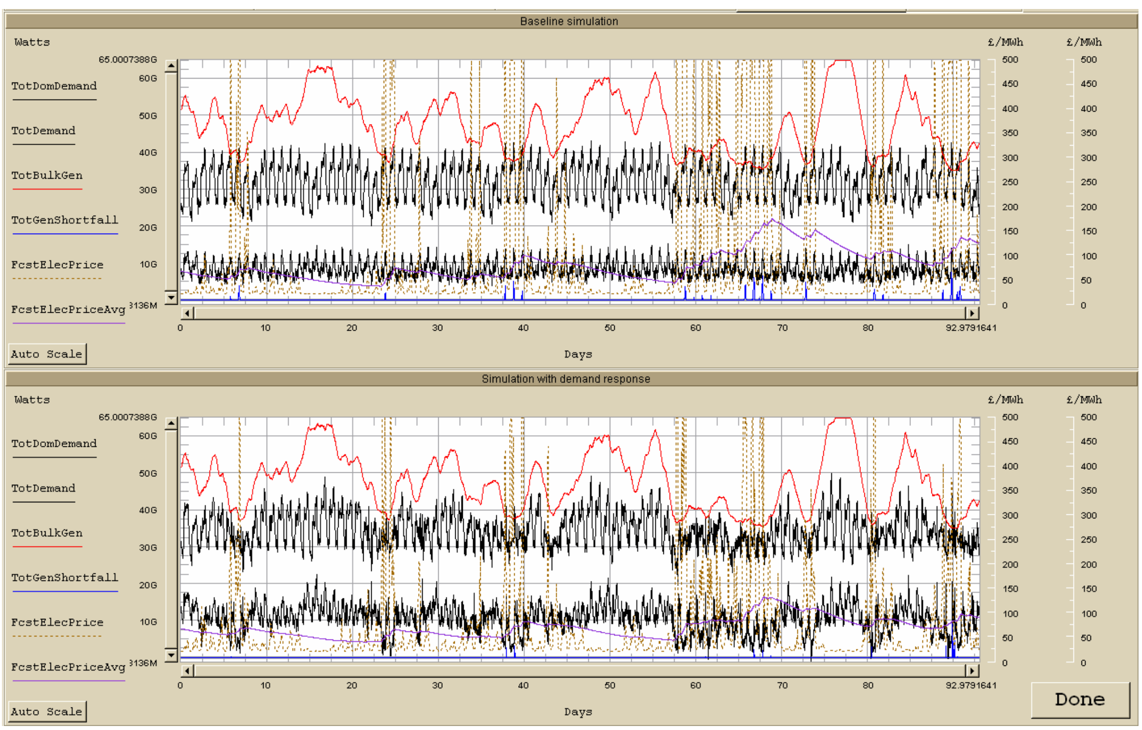


Figure 5-3 Simulation 1 overview

The baseline peak UK demand is about 40GW, which is lower than our current (2003) peak of 50-55GW due to the CHP and solar generation in houses, which accounts for 12-15GW peak (see Figure 5-6 and Figure 5-7). In the baseline simulation, there are a number of times when the overall demand (the upper black line) becomes greater than the available supply. These are times when blackouts would occur, and the total shortfall is represented by the blue line. In the demand response simulation, the overall demand is a much better match to the available supply. Since, in this simulation, the elasticity of industrial and commercial load types was set to 0, this demand profile change is entirely due to the defined domestic elasticities and load shifting. The domestic demand total is shown as the lower black line in each graph.

At times when demand approaches or exceeds supply, the price of electricity rises to peaks. It can be seen that these peaks are fewer and less extreme in the demand response case. The purple line represents the moving average perception of the forecast electricity price. (Remember that the baseline simulation does not actually bill the customer at the dynamic price, but at a fixed 7.5p/kWh).

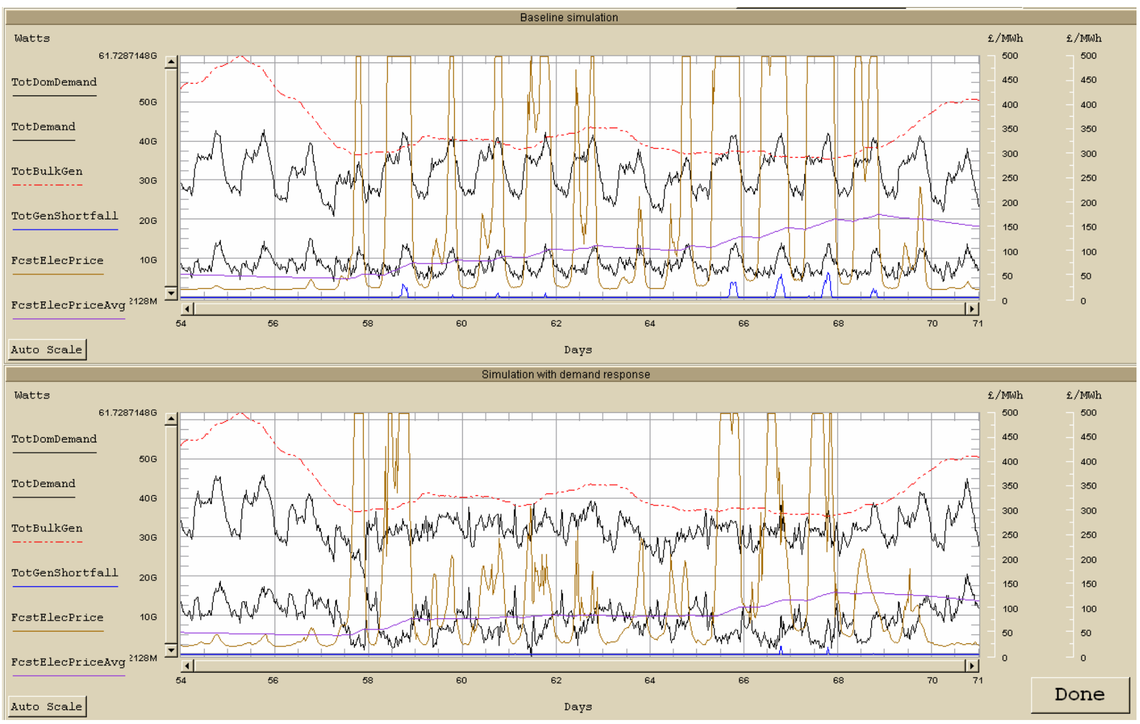


Figure 5-4 Simulation 1 avoidance of blackouts

Above is a comparison of the demand and real-time forecast prices against supply, for the period between days 54 and 71. It is clearly visible that most of blackout periods have been avoided by demand response (the lower graphs), while the real-time electricity price has become more stable. The average electricity price also remains lower during the difficult period by using demand response. At times of plentiful suppy (between days 45 and 58 for example), the price is lower than the baseline 7.5 p/kWh and customers can take advantage of cheap power.

The screenshot below shows how the four main contributors to the domestic demand changes are affected by demand response.

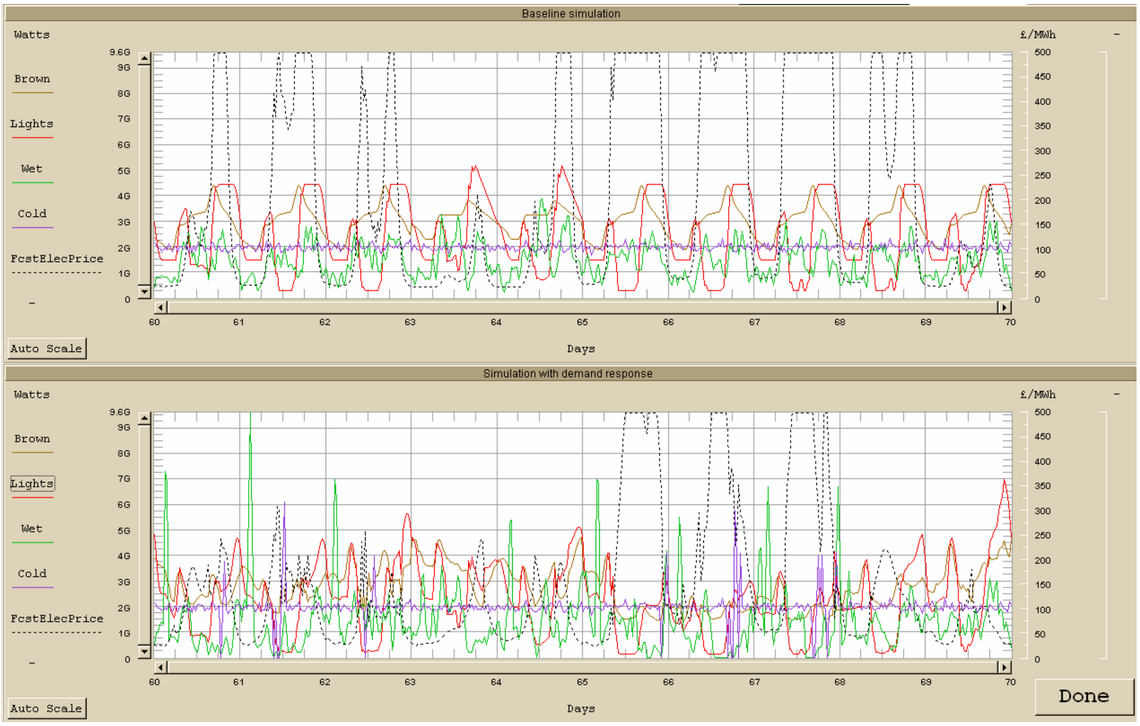


Figure 5-5 Brown, lights, wet and cold load-type reactions in simulation 1

The brown and lighting load-types show elastic behaviour (elasticity=-0.5 relative to demand at a price of £75/MWh). The cold and wet load-types show loadshifting behaviour. The new spikes in demand in the demand response simulation are caused by many customers simultaneously loadshifting to the same cheapest forecast period in the future. This is explained further with Figure 5-8 and Figure 5-9.

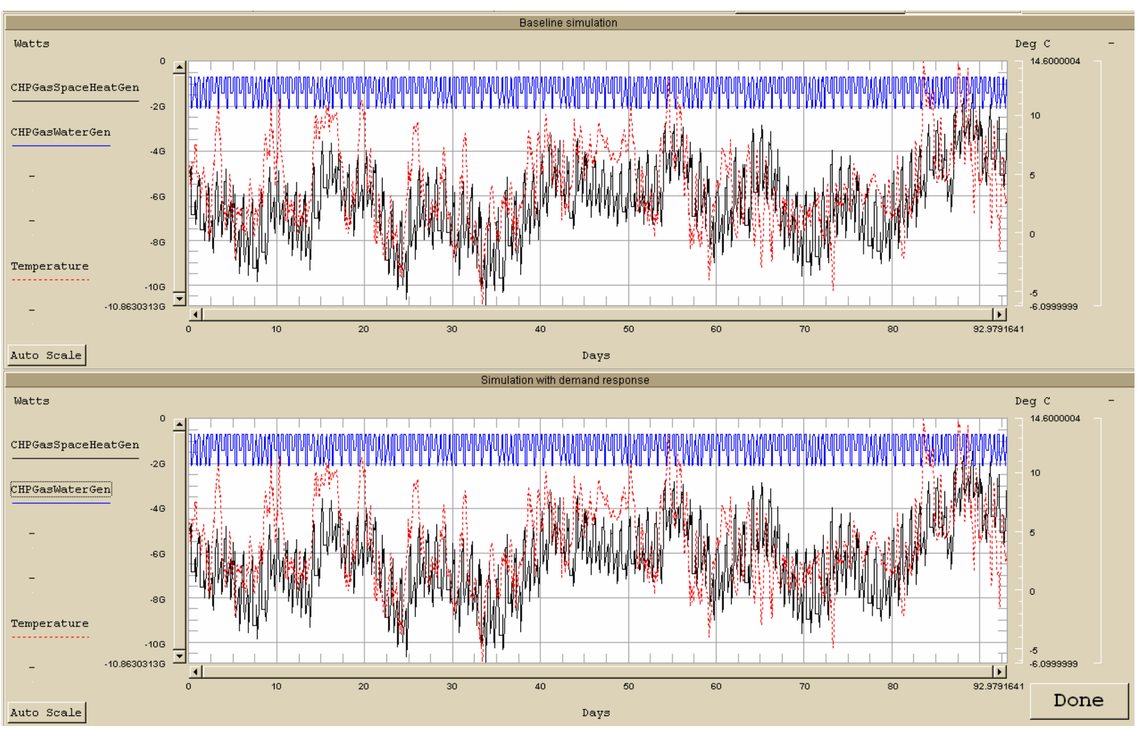


Figure 5-6 Simulation 1 CHP generation (12GW peak)

70% of houses have gas heating, and 50% of these (35% of total) have CHP boilers. The correlation between cold temperatures and CHP generation is clearly demonstrated. Of the houses with CHP generation, each generated of the order of £115 revenue by displaced electricity purchase over the 3-month winter simulation period. This is a substantial sum which would warrant investment in this technology with only a few years payback.

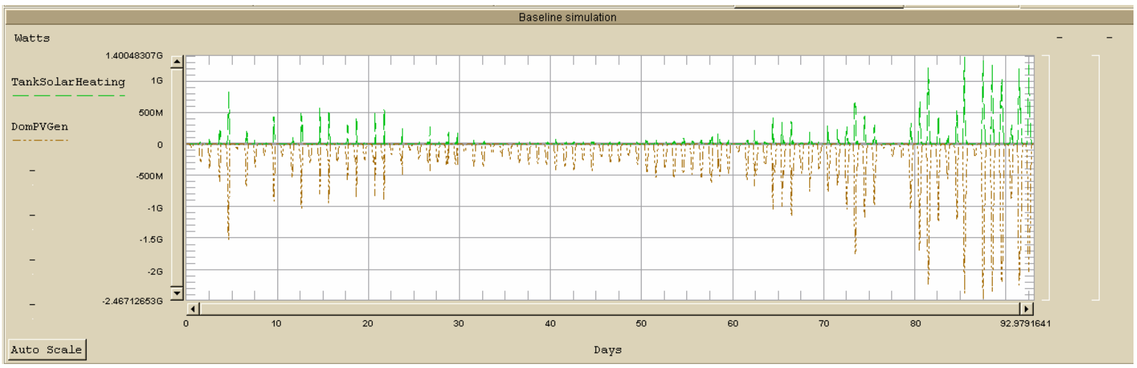


Figure 5-7 Simulation 1 PV generation (2.5GW peak, plus 1.5GW peak displacement)

30% of houses in this simulation have domestic PV installations, but only 5% (30% of 15%) have solar water heaters in conjunction with electric water heating. The peaks of solar generation obviously occur at times of peak solar insolation. Here, direct PV generation is displayed as a negative demand, whereas the solar water heating shows as a positive power.

Of all the 30% of houses that has PV installed, the average load factor during this winter period, accounting for climate data and panel/solar pointing angles was only 6%. Each house with PV saved about £4 of electricity in this quarter by using their panels, whereas the 5% of houses with solar water heating installed saved about £5.50 this quarter (although the load factor of these was less, about 2.5%, because the hot water cannot always be used efficiently). Since both PV and solar water heating arrays were $4m^2$ systems, and taking into account the technology types, it would appear better financial sense to install solar water heaters than PV systems. Neither, however, would appear to be financially good sense at these energy prices.

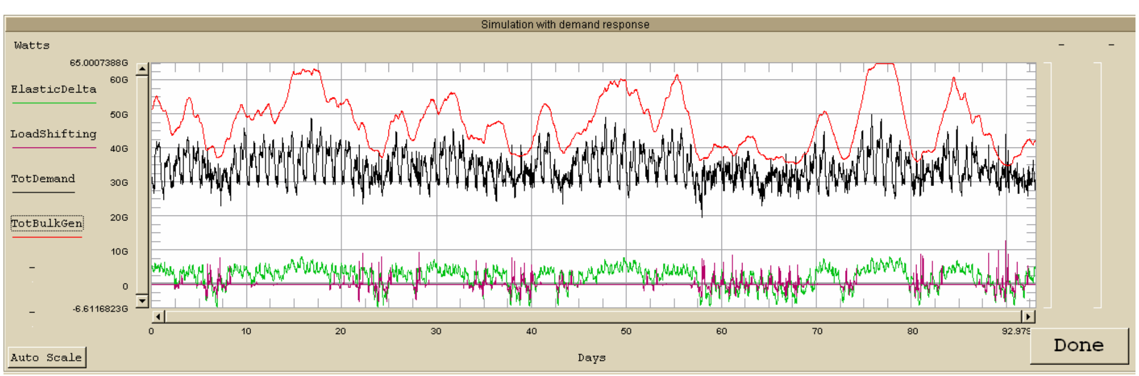


Figure 5-8 Simulation 1 elasticity and load shifting

Here it can be seen that the ElasticDelta (i.e., the demand increase from baseline to demand response simulations), is positive for most of the time, and about 5GW. This means that most of the time, customers are taking advantage of prices that are cheaper than the baseline 7.5p/kWh and are using more energy than 2003 levels. However, at times of high prices, the ElasticDelta is negative, by up to 5GW. This reduces demand and helps to avoid both higher prices and blackouts.

The LoadShifting parameter shows the shift in demand in the demand response simulation, due to cold and wet appliance events that are moved, either due to pro-active load shifting or due to critical peak price events. When prices are low, LoadShifting is zero, but when demand approaches supply and prices rise, LoadShifting becomes significant. The sum total energy integrated across LoadShifting is zero, but the times at which the loads are removed helps to avoid both higher prices and blackouts.

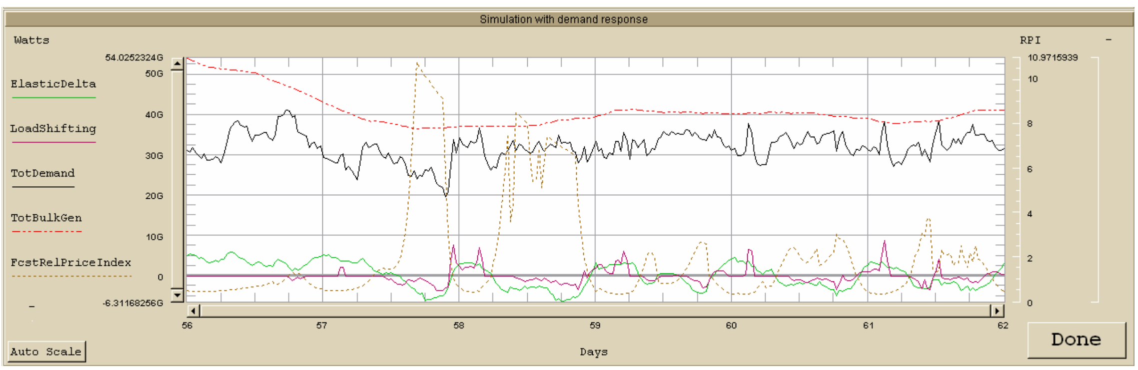


Figure 5-9 Simulation 1 elasticity and load shifting (zoomed in)

This is a focus of Figure 5-8 to show some more detail. The relative price index (RPI) is the forecast price divided by the customer's perception of the average price (which is calculated by weighted, running average). When RPI rises above 3, a critical peak signal is given. It can be seen that the load shifting successfully begins to cause a drop in demand as a blackout becomes imminent on day 57. However, the loads have been shifted and not removed, so they pop up again in the future (for example at day=58.1 and day=61.2). Sometimes, this causes unexpected demand spikes where "valleys" have been converted to "mountains". Since customers, given the choice and the same forecast information, will all load shift to the (same) cheapest period (when RPI is least), this valley to mountain transformation is a real source of concern!

Overall domestic energy consumption actually increases with the use of real-time electricity pricing in this simulation. Below is a table showing how some generic load type consumptions change by moving from the baseline flat-rate system at 7.5 p/kWh to the demand response system simulated here. These figures are taken over the 3-month simulation winter period, so heating figures are larger than the average figures in Table 4-1.

	Baseline use	Demand response use	Change
	kWh/day/house	kWh/day/house	%
Brown	2.9	3.8	+30%
Wet	1.4	1.5	+7%
Cooking (Electrically heated houses only, 60%)	1.8	1.8	
Cold	1.9	1.9	
Lights	2.4	3.2	+30%
Spaceheat (Electrically heated houses only, 15%)	28.8	30.2	+5%
Water (Electrically heated houses only, 15%)	9.1	9.6	+5%
Total domestic loads (all house types)	15.7	17.8	+13%

Table 5-2 Domestic energy use per day in simulation 1

These increases in energy use occurred, despite an overall reduction in average energy bill, over the three-month period, from £109.63 to £108.03 between the baseline and demand response scenarios. This is because the billed price per purchased kWh was a flat rate of 7.5 p/kWh in the baseline scenario, but only 6.0 p/kWh in the demand response scenario. The minimum and maximum real-time prices billed to customers in the demand response scenario were 2 p/kWh and 50 p/kWh. The actual average price over time was 7.1 p/kWh, but customers modified their behaviour so that more energy was purchased at prices lower than average, hence the customers average purchase price was 6.0 p/kWh.

Also of note, for this simulation, is that the overall price averages for the two simulations were:-

	Baseline simulation (billed at 7.5 p/kWh)	Demand response simulation (billed at forecast rate)
Forecast price average (p/kWh)	8.7	7.1
Actual price average (p/kWh)	7.9	5.7

Table 5-3 Forecast and actual price averages for simulation 1

Here, the forecast price average is just what it says, and for the demand response simulation is the billed price to the customer. The actual price average is based upon actual (not forecast) power demands, and is the effective price that the REC companies buy the energy before selling it on to customers.

So, for this case, the flat rate cost of 7.5 p/kWh is not viable for the baseline simulation over this winter period, since the REC's will lose money as they will be supplying energy at a cost to them of 7.9 p/kWh and selling it to customers at 7.5 kWh. Over the summer months, with lower demands, the REC's might turn the situation around and make a small profit, but remember that in this simulation the high domestic CHP generation penetration means that summer and winter demand is roughly equal. In contrast, the demand response simulation presents a financially viable scenario. Energy is sold to customer at (on average) 7.1 p/kWh (6.5 p/kWh after weighting by demand profile), but only needs to be supplied at a cost of 5.7 p/kWh. This represents a profit for the REC companies.

The difference in forecast and actual price averages is simply due to differences between the forecast and actual demand, and is, in the case of this simulation, accidental. The point is worth bearing in mind, however, since any trade at a loss will lead to power trading company bankruptcy and all the associated effects. In a real system, some mechanism, such as a slight over-estimation of demand and/or price, applied all the time, could be used to guarantee that the actual price average was always less than the forecast price average over a reasonable timeframe. Otherwise, power companies will cease trading.

A final fiscal point to examine is the potential financial cost of implementing this kind of demand response, versus simply increasing the amount of firm generation capacity. DRAM [7] estimate that building new plant capacity costs approximately $600/kW, while the cost (see section 3.4.1) of implementing advanced metering is about $100 per household. Analysis of the total capacity shortfalls in simulation 1 shows that about 6GW more firm capacity would be needed to make the baseline simulation blackouts reduce to approximately the same level as for the demand response simulation. Therefore, the costs for the two solutions are about:-

- Add firm capacity: 6GW/1000*$600 = $ 3.6 bn
- Impliment DR: 25 million houses x $100 = $2.5 bn

DRAM [7] estimate that the cost of implementing demand response is only $100/kW (peak demand saved), which is only 1/6 of their estimate for implementing extra firm capacity. Simulation 1 analysis would suggest that the financial balance would still favour demand response as a course of action, but by a much smaller margin. In essence, this analysis shows that for a $100 per household investment, the peak demand saved is not 1kW but 6GW/25E6 = 240W. Of course, the financial benefit of demand response could be calculated as much more if higher elasticities were known or assumed. Here we have been quite conservative.

5.2.2 Conclusions from simulation 1

- Switching 50% of gas (heating) customers to CHP boilers evens summer and winter demand peaks, and dramatically helps to avoid winter blackouts since generation peaks and low temperature minima coincide well.
- CHP boilers will be a good financial investment in the near term.
- Solar PV and solar water heaters are currently very poor investments. Of the two, solar water heaters are probably a slightly better use of capital investment.

- Elasticity and load shifting, in the domestic sector alone and to modest extents, can significantly stabilise electricity prices and help to avoid blackouts.
- Load-shifting of wet and cold appliances, by a combination of pro-active load shifting wet cycles and critical peak shifts of cold and wet appliances, can produce short-term UK demand drops of the order of 4GW. But, correlated “valley-filling” between customers making the same decision and choosing the cheapest forecast time to shift events to, can cause new correlated peaks (of the order of +10GW) where “valleys” otherwise would have existed.
- Real-time pricing of electricity can enable domestic customers to use more energy on aggregate, by taking advantage of lower priced power for the majority of the time.
- In a real system, care must be taken so that the overall billed (forecast) prices do not consistently fall below the actual prices, otherwise REC companies will go bankrupt.
- Implementing demand response will cost approximately £1.5 billion, whereas adding 6GW of extra firm capacity would cost about £2.1 billion.

5.3 Demand response simulation 2 & 3 - without natural gas

Simulation 2 is a hypothetical analysis of a time in the future, when natural gas supplies have either been exhausted or are not available in the UK. In this simulation, the following parameters are used:-

- 2003 fuel prices are still assumed as a reference. The baseline flat rate price is still 7.5 p/kWh, and the price curves are still the same.
- 2003 energy use figures are assumed.
- The elasticity figures used were identical to simulation 1. Industrial and commercial elasticities were again set to 0, which is a pessimistic estimation of the true situation, but allows the simulation to focus purely on the effect of domestic demand response.
- 85% of domestic customers acquire their water and space heating energy from electricity. The energy use is calculated by displacing current gas users. Since, in 2003, gas heating users use on average significantly more energy than electic heating users, this adds significantly to the electrical demand. 15% of homes have no heating (or they have some other fuel than electricity of gas). The analysis tool automatically calculates the new energy use as per Table 4-1 from the percentage ownership figures.
- 100% of domestic customers use electric cooking. The analysis tool automatically calculates the new energy use as per Table 4-1 from the percentage ownership figures.
- Obviously, as there is no gas there is no longer any CHP generation.
- Commercial and industrial electrical load types are modified from 10.7 and 12.2 kWh/house/day on average to 21.8 and 31.5 kWh/house/day, to account for a complete gas-to-electricity fuel switch (as per Table 4-1).
- Domestic solar water heating uptake is raised to 60% of households, with 8m^2 panels (5kW peak).

- Domestic PV uptake is raised to 60% of households, with $16m^2$ panels (2.4kW peak).
- 60% of households are equipped with 20kWh electrical storage capacity. Currently, the most viable practical realisation of this would be an electrolyte store so that lead use is minimised. Maximising storage energy and round-trip efficiency is of paramount importance (along with cost and practicality), but the peak power input/output is not required to be large. In fact, large peak inputs/outputs can be extremely bad for system stability.
- 100% of households are assumed to have switched to a demand-response water tank and heating system. The houses now get all their water heating AND space heating requirements from their electrically heated tanks, via a standard central heating arrangement. The tanks are 400 litres (compared to a standard tank today which is often 120 litres), but they are insulated so that the average heat loss is less than a normal 120 litre tank. The operation of the tanks is described in more detail in section 4.9.2. Essentially, the tanks try to buy power when it is cheap, and try to use stored energy when power is expensive. However, they will always attempt to deliver demand requirements whatever the energy price.
- 80GW of wind capacity (as per Table 2-4)
- 100GW of firm capacity. This is thought made up of 20GW (wave) + 10GW (wood) + 1.5GW (hydro) + 0.1GW (tidal) + 0.2GW (organic waste) + X
- X = 68.2 GW. Where this comes from is open to debate and this thesis does not propose to provide any solutions! Coal, nuclear, fusion, or some further firm renewable capacity. Ideas on a postcard, please. Unless we are prepared to lower our overall energy use, the UK needs to find an extra 68GW of capacity!
- 100 discreet houses are modelled. Since all houses have electric space and water heating, the idea is that 100 discreet houses provide a big enough sample to provide a smooth load curve of quantised wet, cold, water and spaceheat demands.
- Simulation 2 occurs over the same 3-month winter timeframe as simulation 1 (see Figure 5-2).

There are a few key parameter decisions that determine the success or failure of the demand response simulation due to stability constraints (see section 4.8 for more description of stability problems).

- The power rating of the immersion heater element in the water heaters is crucial to the stability of the system. A standard 3kW element is not sufficient to supply the average water heating plus space heating requirements of a house. However, doubling the value to 6kW causes the reaction of the population to price to be extremely severe. 25 million households switching 3kW together amount to a 75GW demand change, whereas 6kW elements could result in a 150GW demand change! Pre-analysis of simulation 2 parameters showed that an element power of about 4kW was required to keep unsatisfied household water demand within a reasonable level, while still achieving some kind of system stability.

- Even by optimising the immersion heater element powers, the system was still difficult to keep stable. For this reason, the HIGH price curve was used for the demand response analysis (see Figure 4-13 and the blue line in figure below). The high price curve has a lower gradient and thus leads to less likelihood of oscillation and instability in the system. The big disadvantage is that it raises prices somewhat unnecessarily when demand is of the order of 0.5 to 0.8 of capacity. The selection of the optimum price curve is a tough compromise between the availability of cheap power and the requirement for stability. Only very robust forecasting algorithms will allow price curves with very sharp knees such as the red (MID) curve below to be used without system instability becoming a problem.

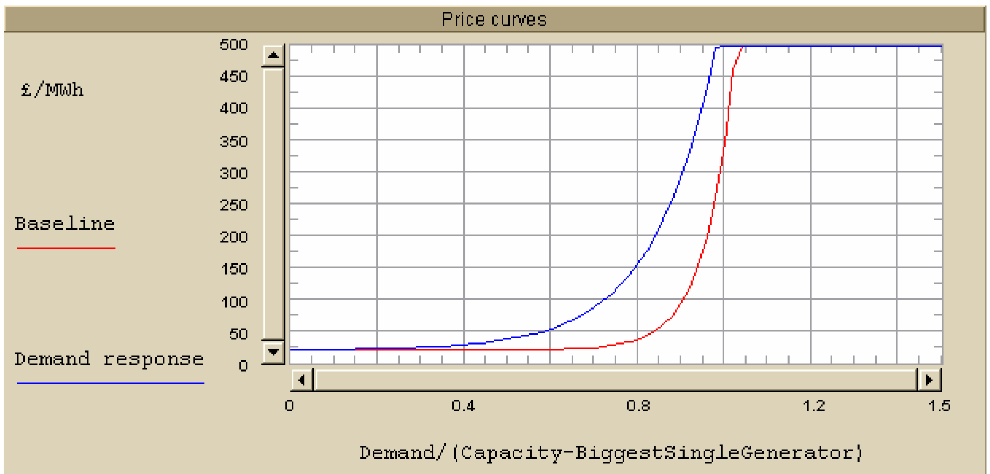


Figure 5-10 Price curves used for simulation 2

- Finally, although the domestic electric storage capacity was defined as 20kWh per house, the optimum power flow rate input/output was found to be about 200W per house. This allowed a reasonable overall power flow (60% x 25 million x 200W = 3GW) while still allowing the storage to supply power steadily for 100 hours (4 days). There is little point (from a network standpoint) of having storage discharge in a matter of hours, if supply shortages can last for several days. The lower power flow also helps to keep the system stable, whereas high power flows can cause instability with the current forecasting algorithm.

5.3.1 Simulation 2 results

It is interesting to first present the results of simulation 2, but using the MID price curve. Terrible instability problems are seen, due to the steep gradients of the price curve combined with the high degree of customer response available!

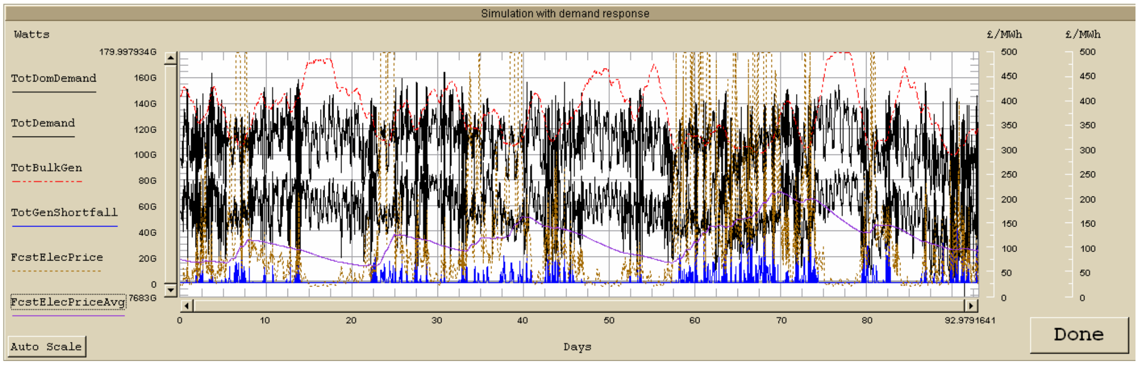


Figure 5-11 Simulation 2, demand response instability when using the MID price curve

Below is a zoomed part of the above graph set to show an example of the oscillation more clearly.

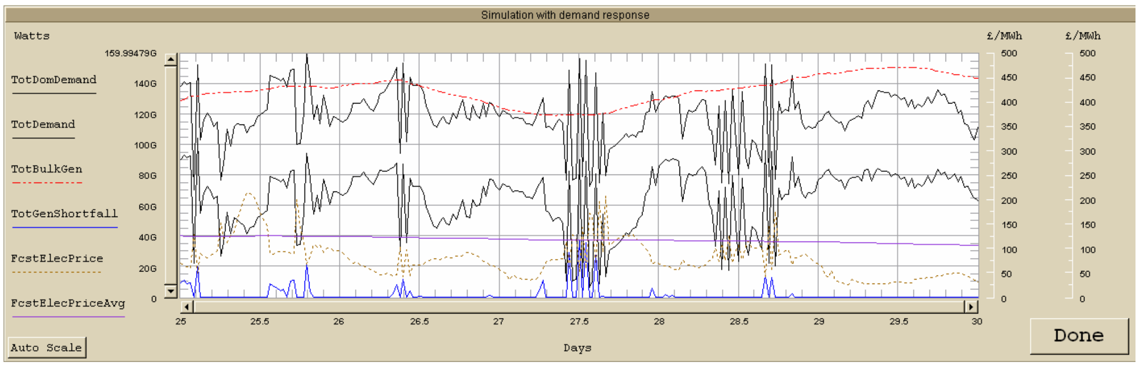


Figure 5-12 Simulation 2, demand response instability when using the MID price curve

The system is much more stable when the HIGH price curve is used, and this is the result set discussed in the following text. Below are shown the baseline and demand response simulations for this scenario. The peak demand occurs on day 24 due to low temperatures (see Figure 5-2), and is about 160GW. Peak generation capacity is 180GW (100GW firm plus 80GW wind), but the actual available capacity rarely reaches this amount due to variable wind speeds.

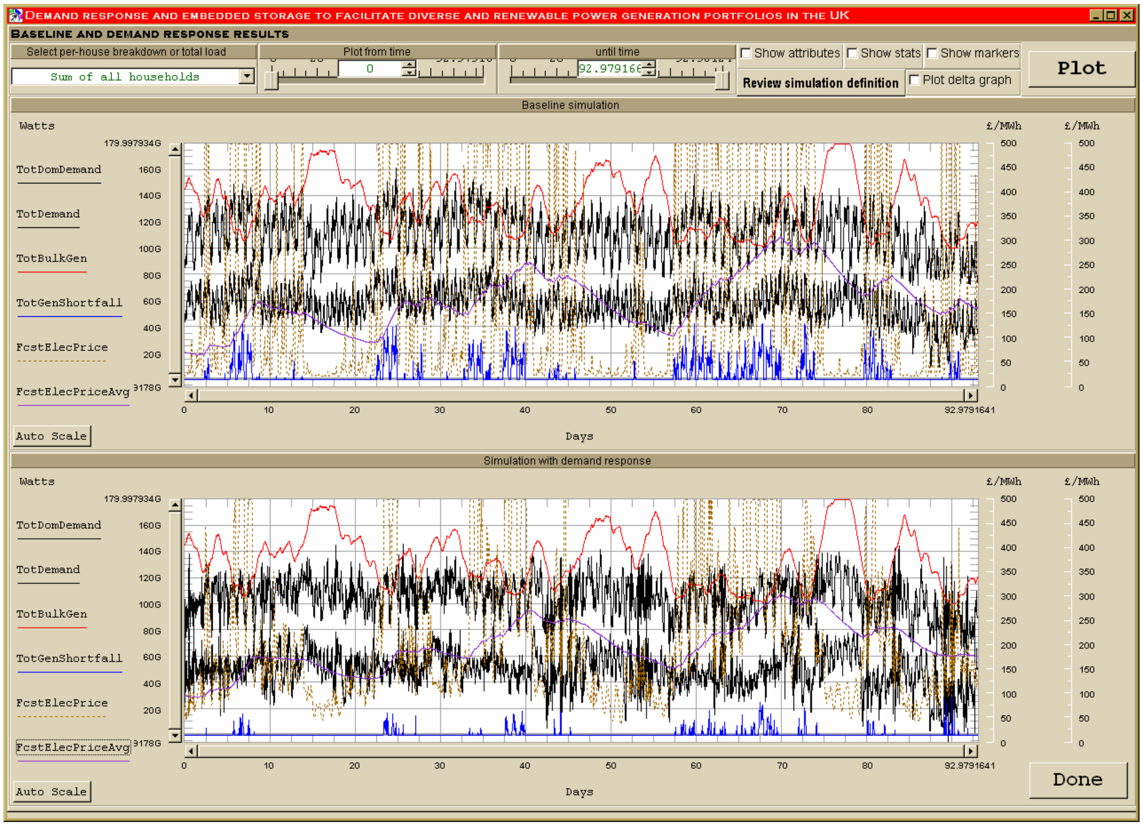


Figure 5-13 Simulation 2 overview

The lower black lines on each graph set show the total domestic demand, while the upper black lines show total overall demand (domestic + commercial + industrial). The blue line shows the overall generation shortfall. Quite clearly, the demand response simulation shows a much better match of demand to supply. The blackout period durations and magnitudes have been reduced dramatically. The average unsatisfied demand rate in the baseline simulation was 3.1% (kWh/day unsatisfied divided by average kWh/day demand). In the demand response simulation, the unavailability reduced to 0.6%.

To show the effects more clearly, it is useful to concentrate on the period from day 50 to day 80, since this contains a period of sustained supply shortage over 10 days, with more plentiful energy supplies both before and after. The overview of this time period is shown before, both for the baseline and the demand response simulation.

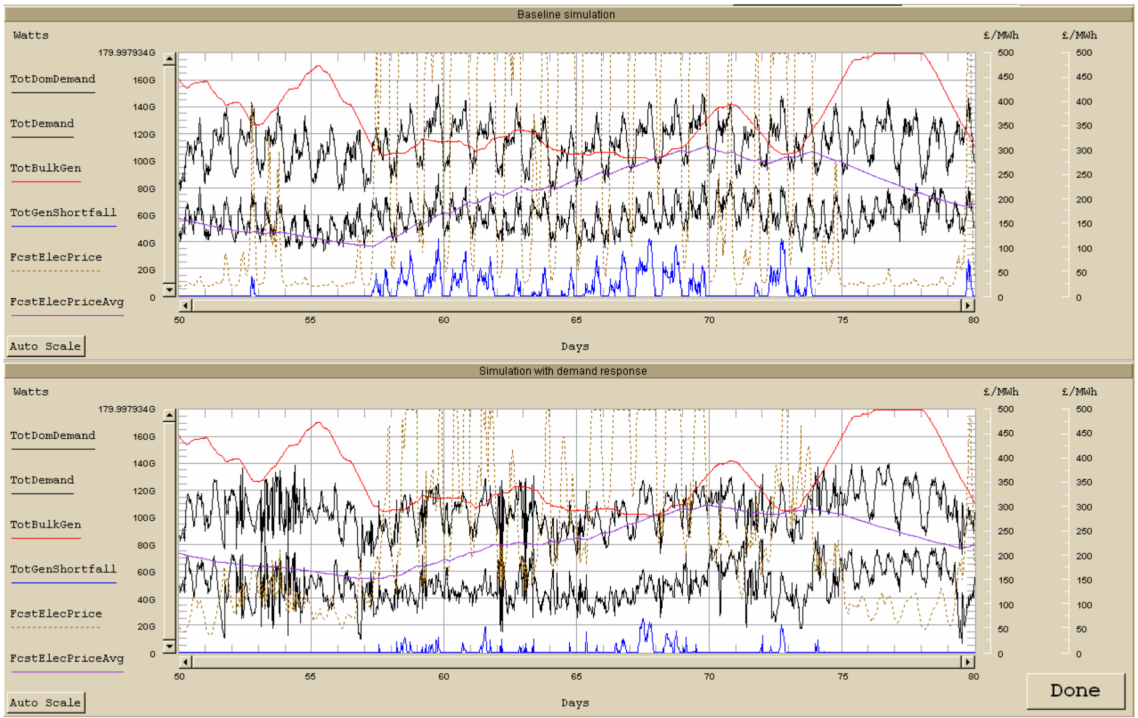


Figure 5-14 Simulation 2 overview (day 50 to day 80)

Below, it can be seen that domestic PV generation peaked at 23GW and solar water heating displaced a peak demand of 18GW, but during the difficult period between days 58 and 70, the electrical PV generation peak is only about 5GW peak, with a solar water displaced load of about 1-5GW peak. Of course, these peaks only occur during the hours of direct sunlight which are few and far between in winter.

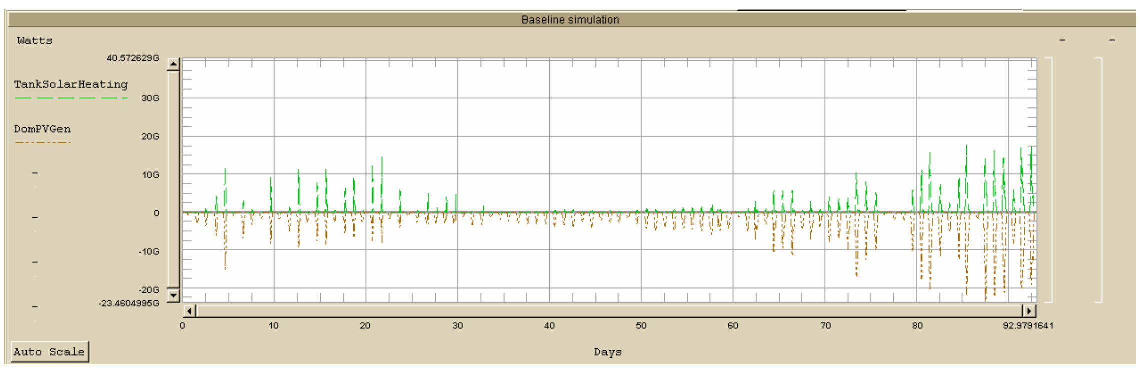


Figure 5-15 Simulation 2 PV generation (23GW peak, plus 18GW peak displacement)

For simulation 2, the overall price averages over the 3 months, for the baseline and demand response simulations were:-

	Baseline simulation (billed at 7.5 p/kWh)	Demand response simulation (billed at forecast rate)
Forecast price average (p/kWh)	18.7	20.8
Actual price average (p/kWh)	18.1	21.5

Table 5-4 Forecast and actual price averages for simulation 2

As opposed to simulation 1, this time the demand response average prices are higher than the baseline averages. This is mainly because we were forced to use the artificially high price curve for the demand response simulation, in order to achieve some semblance of stability. If we could have a better forecasting algorithm and use the mid price curve, lower average prices could be achieved.

This table contains a key point. In these simulations we have assumed that fuel prices and baseline energy use remain at 2003 levels. The assumption of constant fuel prices allows us to use the price curves in Figure 4-13. If fuel prices changed, we would have to set new curves. However, in simulation 2 the average prices over the 3-month period are way above 7.5 p/kWh, the 2003 flat rate for electricity. This is because, for large portions of the simulation, demand was close to or above the supply capacity. This raised prices due to the market effects shown in Figure 4-13. Clearly, a 7.5 p/kWh flat rate to customers over this period would leave any energy supply company (REC) in massive debt. The baseline simulation using this flat rate is completely unworkable (the flat rate would have to be raised to about 19 p/kWh). The overall average price could be reduced in this simulation by simply adding more supply capacity arbitrarily to reduce the pivotal seller market effect, but the point of these simulations is to show the effects of constrained generation and how demand can be adjusted to meet these limits. In reality, adding extra demand capacity also costs money (c. $600 per kW) and this will raise energy prices across the board.

Even in this simulation, with an unworkable flat rate price of 7.5 p/kWh against an average cost in the region of 20 p/kWh, the demand response customers managed to benefit a little from cheaper power. They bought power, on average, at 19.9 p/kWh by changing their behaviour. The baseline customers, however, if they had been paying for the power at true forecast prices, would have paid 20.5 p/kWh on average.

The chart below shows the change in customer energy use between the baseline and demand response scenarios in simulation 2. Because the prices are higher than the 2003 flat rate cost of 7.5 p/kWh, the overall energy reduction is lowered due to elastic effects. Customers are saving energy to save money!

	Baseline use	Demand response use	Change
	kWh/day/house	**kWh/day/house**	**%**
Brown	2.9	2.0	-30%
Wet	1.4	1.3	-10%
Cooking (100% of houses)	2.0	1.8	-10%
Cold	1.9	1.9	
Lights	2.4	1.7	-30%
Spaceheat (100% of	36.2	40.0	-12%

houses)			
Water (100% of houses)	9.5		
Total domestic loads (all house types)	56.3	48.8	-13%

Table 5-5 Domestic energy use per day in simulation 2

The demand response customers, on average, spent a total of £882 pounds per household over this 3-month period. The baseline customers, if they had been billed at a workable flat rate of 19 p/kWh, would have spent £971 on average. The demand response customers save money, but these bills are high relative to current 2003 bill levels. This will likely be the effect as gas (for sale in 2003 at 1-2 p/kWh) begins to run out and a mass switch to electricity is mandatory (unless we can use coal or nuclear mass CHP systems).

As outlined previously, in simulation 2, all customers have large (400 litre) hot water tanks and 60% of customers have domestic electrical storage (20kWh). By buying power at cheaper times (and selling it at expensive times in the case of electrical storage), the houses can attempt to profit from power trading.

Below is a graph set showing the combined electrical demand of the immersion heaters in all houses. The water and spaceheat demands shown here are energy demands by customers from the tank, and are therefore are not direct electricity demands. The water and spaceheat demands take hot water energy from the tank, and the water tank model (section 4.9.2) decides when to turn on the immersion heaters for each house. In reality, this decision would be made by a small computerised panel in each individual house, with parameters customisable by each user. The customisable parameters are important because it provides diversity amongst the customers, which is essential for network stability.

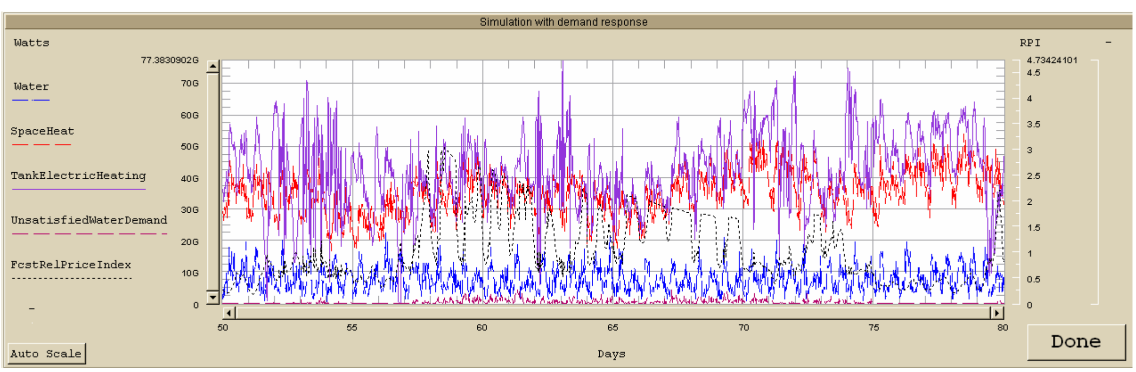


Figure 5-16 Simulation 2, water tank demands and heating (day 50 to day 80)

This diagram isn't particularly clear, but it should show that the electrical demand placed by the immersion heater elements tends to be less when the relative price index (RPI) is higher. What this graph does show clearly is the trace of "UnsatisfiedWaterDemand" which is an amount of desired hot water or spaceheat energy which is not available from the tank at any time. This trace is nearly (but not quite) zero at all times in the baseline simulation. The times when it is not zero is equivalent to the real-life situation where the immersion heater tank runs cold when a second person tries to run a bath – the immersion element does not have enough power to heat the water fast enough for back-to-back full-power demands. In the demand response simulation, both hot water and space-heat demands need to be met by the immersion heater element. This is why the element power was raised to minimise the "UnsatisfiedWaterDemand" from 3kW to 4kW. Ideally, this figure would be more, maybe 6kW, to ensure that customers never have cold baths. However, the current forecasting algorithm available does not allow such high responsive power demands without instability problems.

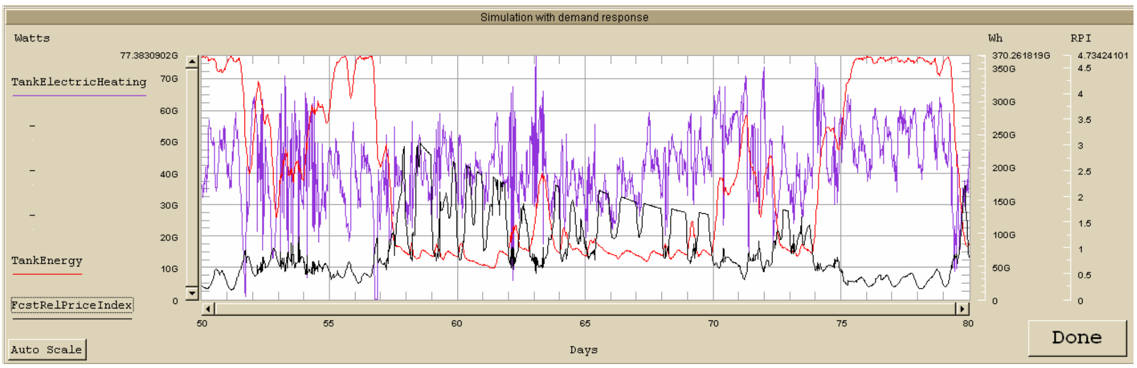


Figure 5-17 Simulation 2, water tank stored energy (day 50 to day 80)

The graph above shows more clearly that the effective stored energy in the water tanks (averaged over all the households) rises towards a maximum level when the prices are low (relative price index, RPI <1). During this time, the heater elements will be on and the tanks will fill to their maximum levels. When prices are high (RPI>1), customers will try to use hot water from the tank without adding energy, and the tank temperatures drop. What can be seen here, however, is that the tank stored energy, for these 400 litre tanks, only lasts for a day or so. This is useful for riding through shorter periods of high prices (related to the time of day), but is not much use over longer periods such as the 10-day demand shortage between days 58 and 70.

An approximate financial revenue generated by having the 400-litre storage tanks over the three-month period can be calculated. To do, this, take the total electriticity cost of the customer water and spaceheat demand profiles, which will be biased towards the time of energy that the customers uses. Now compare this to the total cost of electrical energy purchased to heat the tank. For this simulation, the numbers are £811 and (£762+£19=£781), where the £19 is the energy saving cost due to the solar water heater over the time period. The difference between £811 and £781 is £30, which is the customer saving due to having hot water storage. Over a year, £120 might be saved. Over 5 years, £600 might easily pay for such a tank installation and this would represent a reasonable financial investment for the customer.

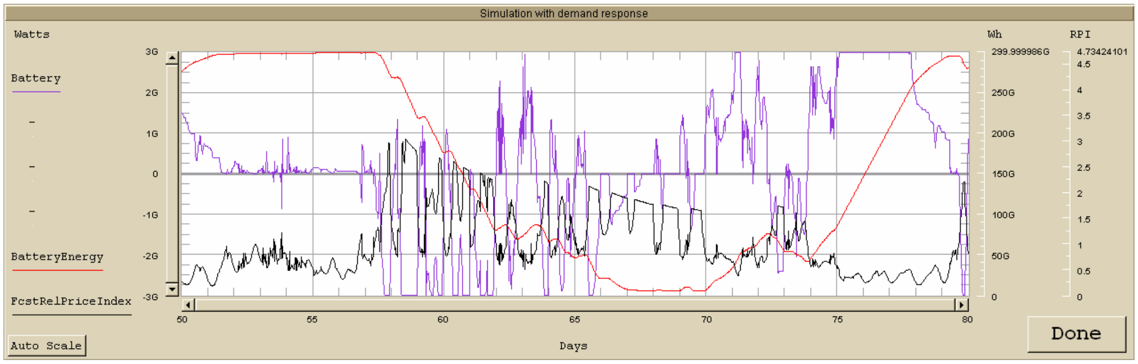


Figure 5-18 Simulation 2, battery stored energy (day 50 to day 80)

We can examine the effect of the electrical storage in a similar manner. The above graph shows the total power flow to and from domestic electric storage (60% of households with 20kWh of storage, at a maximum power of 200W). The 200W was artificially constrained so that the price-demand system was stable, and also so that the 20kWh of storage, at 200W, would last a reasonable time (20kWh/200W = 4.2 days). The graph shows that the domestic storage was filled when the relative price (RPI) was low. On day 57, as demand rose towards capacity, the RPI rose and houses began making the decision to release their energy. The release of energy reduced the supply deficit and helped to stabilise prices. By day 67, the storage was depleted, but fortunately, by day 71 the RPI was again low enough that customers began replenishing their stores. The timeframe between day 67 and day 71 would represent a period of high risk of blackouts, with depleted reserves and high prices.

The cost benefit of electrical storage can be assessed by examining the overall customer revenues from the buying and selling of power. Of the 60% of houses with electrical storage, the average power flow over the 3-month period was 85W, which equates to a storage utilisation “load factor” of about 40%. Average customer revenue was about £20.30 over the quarter, so possibly £80 over a year. With an installation cost of ~= £6000-£12000 for the 20kWh storage (see appendix 7.3.1) this represents a 75 year payback at current prices, even without considering discount rates!

Another important factor to consider is the customer revenues due to the electrical power trades, as a function of their power trading behaviour. As described in sections 4.12.1and 4.12.2, each individual customer in the simulation is assigned a random threshold of the relative price index (RPI) at which to begin buying power. This threshold is between 0.5 and 0.95 for each customer. A threshold of 0.95 corresponds to a more conservative approach but with higher load factors of the storage use. A threshold of 0.5 corresponds to a customer who will hold off buying and selling until prices are very high or very low, with the aim of achieving higher revenues per unit bought and sold. It is possible to extract the revenue per customer and plot this against their individual buy threshold prices, and this is shown below.

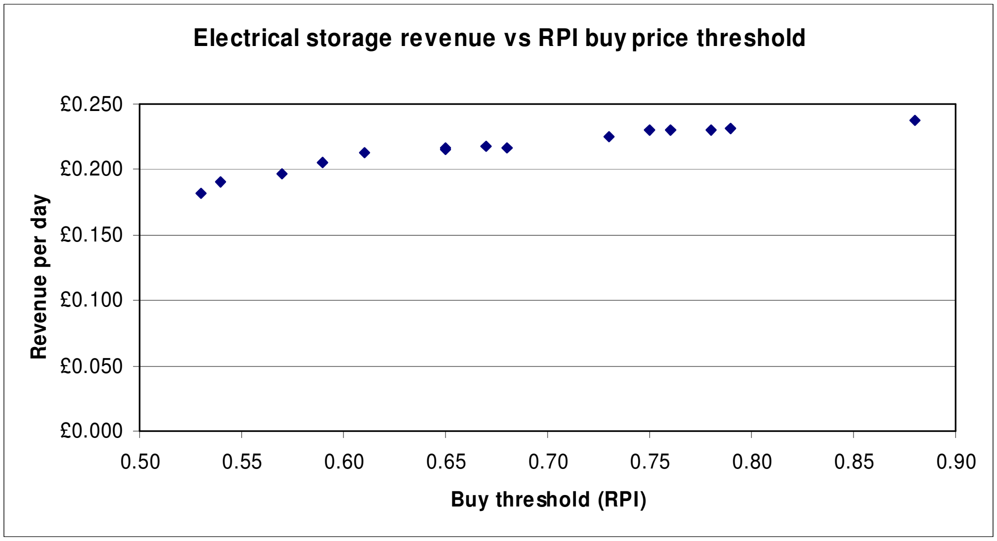


Figure 5-19 Simulation 2, revenue due to electrical power trades

It can be seen here that the more aggressive customers actually received less revenue per day due to power trading than the conservative customers. This is due to the lower “load factors” of the storage which is exercised less often, and the curve causes a minor problem since customers will therefore all tend to use thresholds grouped around the 0.8 to 0.95 region, thus removing some diversity from the population. This removal of diversity means that network instability is more likely due to mass coordinated buy/sell decisions. Also, having no customers holding back their storage until the price rises to very high peaks means that no storage capacity may be reserved for longer periods of supply shortage. Some mechanism might be required to offset this behaviour. A possibly solution would be a legal regulation of storage capacity to power ratio (to guarantee that storage would take at least X days to charge and X days to discharge). This would also have the beneficial effect of enhancing network stability as described in section 4.8. An alternative viewpoint is that a price differential in power buy/sell prices should change the shape of this curve and incentivise more aggressive price trading at the expense of the more conservative approach. Also, the round-trip efficiency of the storage is less than unity, which essentially adds a trading charge which will help to modify the revenue curve to favour buying and selling and larger profits. Some of these effects are not seen in this simulation since the maximum storage charge/discharge power of only 200W means that customers with conservative buy/sell patterns and customers with aggressive buy/sell patterns tend to be merged since the stored power takes many hours to buy and sell. Further analysis would be required to analyse these possibilities, to further understand the economics of buy and sell behaviour, and whether higher power flows enabling quicker buy and sell patterns would be beneficial or destabilising.

For simulation 2, the fiscal benefit of investing in demand response technology, as opposed to investing in new generation plant, can be re-evaluated. The cost of investing in demand response is still \$2.5 billion (25 million houses x \$100 from section 5.2.1). For simulation 2, the additional firm capacity required for the baseline simulation, over the demand response simulation, to provide approximately the same level of blackout avoidance, is about 35GW. At \$600/kW cost of peak capacity, this would cost $21 billion. Clearly, demand response is a cheaper system in this scenario.

Simply relying on extra plant capacity would also be extremely inefficient of capital investment since the baseline simulation shows a delta between demand peak and demand minimum of 90 GW (72 GW minimum to 162 GW peak demand). It would be nice to prove that the demand response simulation showed a smaller swing but in fact the simulation here shows a larger demand swing of 93GW (53GW to 146 GW). This is due to demand “outliers” caused by some oscillations in the price-demand feedback loop that have not been fully damped, combined with some new demand peaks that have been caused by correlated load shifting. Simulation using a better forecasting algorithm and a better load shifting algorithm ought to be able to show a lower achievable demand swing.

5.3.2 Simulation 3 – increased customer elasticity

A final simulation presented here is that of simulation 2, rerun with the following small changes:-

- The domestic cooking, wet, water heating and space heating load type elasticities increased from -0.1 to -0.2.
- The commercial and industrial sector elasticities set to -0.2 (0.0 in simulation 2).

Very briefly, these slight increases in elasticity produce an even better matching of demand to supply. The graphs sets below should be compared to Figure 5-13 and Figure 5-14. It is impossible to evaluate the added cost benefit of this increased degree of flexibility in demand, since customer behaviour and elasticity is impossible to cost. However, the reduction in blackout periods and price volatility is clear. The unavailability is reduced to about 0.04%.

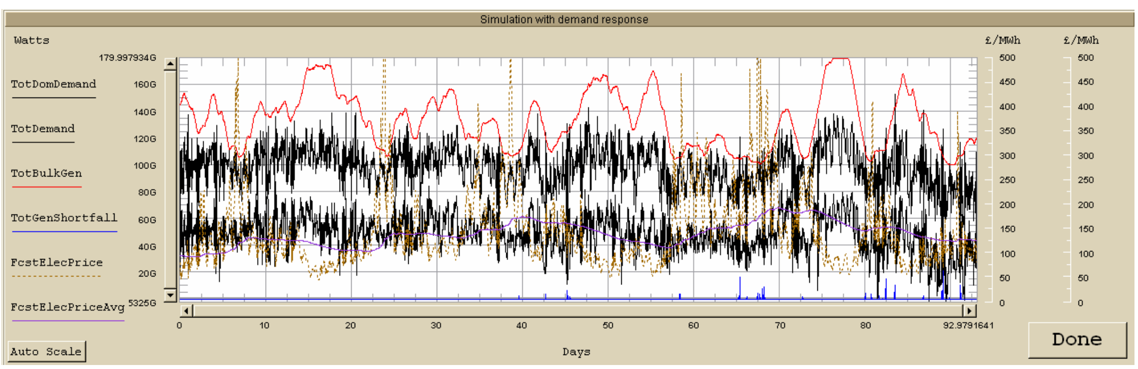


Figure 5-20 Simulation 3, effect of slightly increased assumed elasticity

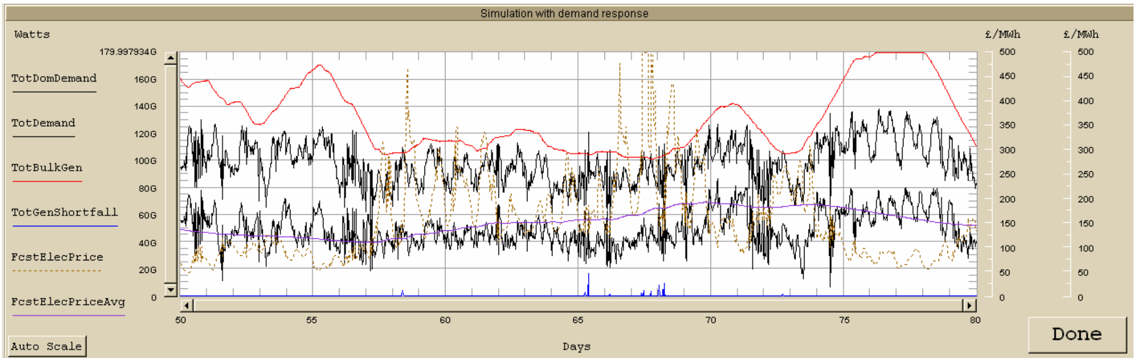


Figure 5-21 Simulation 3, effect of slightly increased assumed elasticity (day 50 to day 80)

5.3.3 Conclusions from simulation 2 and 3

- A much better forecasting algorithm is required for electrical demand. It needs to take into account the effect of price changes on future demand, to avoid instability and oscillations in demand and price.
- UK winter peak electrical demand, after a 100% gas to electricity fuel switch, will be about 160GW. This figure assumes that the transport sector continues to be a petrol and DERV economy.
- With high penetrations of wind power (80GW), we can expect supply shortages to last of the order of 10-12 days.
- High penetrations of installed domestic PV and solar water heating will only produce 15-25GW peak each, during the best winter periods, and much less during the worst winter periods.
- Market forces will play a proportionately more important part in electricity pricing as supply becomes more variable, tending to increase prices by altering the operating points on the price-demand curve. Any rises in bulk fuel prices will push the price-demand curves up vertically.
- Domestic hot-water storage tanks will need to be bigger than 400 litres in order to ride out multiple-day periods of supply shortage and high prices. However, analysis suggests that customer savings with these tanks merely to enable single-day storage can be financially large enough to pay for their installation. The technology is simple; there are no chemicals, high pressures or high technology parts.
- Domestic electrical storage is desirable and controllable, but is unlikely to offer a good financial return unless storage hardware prices fall by more than 4x or electricity price volatility, at the customer, rises by an appreciable degree. Further analysis is required to examine the revenues curves generated by such storage to avoid mass bulk buy/sell decisions which might decrease network stability.
- Slight increases in customer elasticity (to ~=-0.2) in the cooking, heating, commercial and industrial sectors can produce a surprisingly good matching of demand to supply.

5.4 Extension to analyse local grid constraints

To this point, all analysis and comment has been organised around a UK-wide scenario. The simulations have analysed only the total power available and consumed within the entire UK at any instant in time. The price calculated has been dependent only upon the balance between these two bulk parameters, and no account has been taken of problems that will occur if there is excess generation within one area of the network and excess demand within another area. On a local scale, these effects must be accounted for, in order to avoid system overloads, voltage rise or blackouts.

Future research in this area could be carried out relatively easily with this model, by analysing smaller populations as sections of the network. This could be done at the BSP (Bulk supply point) level, by considering the BSP as a traditional generator with a peak capacity equal to the capacity of the BSP. The analysis tool could usefully be extended, for areas in which excess generation might be expected, so that it checked for excursions of power export limits as well as times where demand power exceeded power import limits. Within these smaller sub-networks, it is conceivable and likely that local prices might deviate from prices at other parts of the network. Each sub-network will typically have different:-

- total available (import or export) power limits
- demand profiles
- and also, possibly, different generators selling to the network, depending upon the network financial structure

Since these three factors determine the price of power, it is quite reasonable to expect different geographical areas to have different power prices in real-time. These different prices could be calculated by the REC or DNO companies in real-time by using network data and overall generation data from NETA. In this way, blackouts due to local grid constraints could be avoided without unnecessarily affecting the prices and customer behaviour in distant parts of the grid.

6 Conclusions

The results of this work suggest that demand response is a more effective solution to the problem of variable supply and demand than simply adding extra peak capacity with poor load factor. In the near to medium term, implementing demand response in the UK will cost of the order of £1.5 billion whereas adding 6GW of firm capacity would cost approximately £2.1 billion. Since all customers will benefit from the resulting stabilisation of electricity prices and the avoidance of power blackouts, there is no economic argument for not spreading the cost of bulk implementation (installation of advanced metering in all domestic properties) amongst all UK power users, irrespective of their participation in any real-time pricing programme.

In the longer term, as renewables play an ever larger part in our power portfolio, and natural gas becomes less available, demand response will become even more attractive as a method of ensuring security of supply, as it allows available generators to operate at higher load factors and efficiencies by matching demand to supply rather than supply to demand.

The biggest barriers against exposing domestic customers to real-time electricity prices are the social and political acceptability issues. These are mainly perception issues and could be overcome by a well designed communication of the financial impacts to different customers. The main concern would be any perceived negative impact on “fuel poverty”, the retired and the infirm. It has been shown that demand response actually allows customers enrolled in real-time pricing programmes to spend less on power than customers paying flat rates. This is because flat rates include premiums to cover the variable prices, and avoidance of the flat rates therefore avoids the premiums. The unemployed and retired, in general, will be more able than more wealthy people to modify their electrical time-of-use behaviour with regard to electrical power, and hence should be in a prime position to benefit from real-time pricing. However, for any real-time demand-response programme to be politically acceptable, it would have to be (at least initially) a voluntary programme. Within a few years of operation, it is anticipated that most customers would voluntarily switch to real-time pricing in order to save money. Wealthy people with inflexible schedules would be the least likely beneficiaries from real-time pricing. From this perspective, demand-response is “socially inclusive” but the initial public acceptance of this might be hard to achieve.

This report has examined the possible costs and effects of mass domestic participation of UK households in a real-time price demand response programme, along with potential implementations of domestic energy storage options and renewable generation scenarios. The analysis has been carried out by developing a significant software tool to simulate portfolios of bulk and domestic generation, embedded storage, and demand response. Demand response can be achieved by either conscious human behaviour changes (eg. switching off an unnecessary light when electricity is expensive), or by programmable domestic control panels which might control washing machines, fridges, immersion heaters or electrical storage devices.

It has been found that domestic energy storage is difficult and expensive to achieve in any useful quantities relative to our energy use, particularly when a mass gas-to-electricity fuel switch is imagined. Of all the storage options, domestic hot water storage is the most financially viable solution at present, but this does not particularly help ride out supply capacity shortages of more than a day or so in winter periods unless water tanks larger than 400 litres per household can be installed. Domestic battery (or electrolyte store) storage offers a more controllable but much less financially attractive solution, also requiring unattractive hazardous chemicals present in large quantities. Other electrical storage methods are even less financially viable. The presence of appreciable embedded storage capacity in the domestic sector increases the possibility for network instability driven by a population that makes mass correlated buy/sell decisions. The stored energy quantities must be examined separately from the maximum power flows storable or releasable from the storage. Large amounts of stored energy are highly desirable, but it is not desirable from a network stability standpoint for this power to be releasable en masse over short timeframes at high powers. It might be necessary to regulate, by law, the ratio of stored energy to power flow rating in each domestic storage installation, so that energy stored is only releasable over many hours or days, and not over minutes.

A large part of the work involved in this report surrounded network stability, price stability and the avoidance of blackouts. This report concludes that the issue of demand forecasting will play an ever important part of any demand-response programme. The demand forecasting algorithm used in this report was limited in its capability to account for the feedback loop formed by price and demand. As a result, it was necessary to compromise the available customer responses, embedded storage configurations and price curves in order to avoid devastating oscillations in electrical demand. Creating a more effective, adaptive demand forecast will be essential to future network stability. The demand forecast will be used to set price, and these price forecasts might also be modified on a region-by-region basis to account for local grid constraints. The price forecasts also need to be monitored and possibly adjusted upwards slightly, to ensure that the overall price averages enable generators and power companies to operate profitably. The price forecast might need to be asymmetric, i.e. able to react quickly to a rise in demand, but more slowly to a drop in demand, in order to provide the best avoidance of blackouts while still avoiding price oscillations.

Overall, this report finds that passing on real-time electricity prices to the customer, thereby exploiting the natural human tendency to save money and buy cheaper power, is a much more effective solution to a future energy supply/demand problem than by simply making mass capital investment in complicated generation and storage solutions. Relatively small modifications to our electrical demand behaviour, such as allowing washing machines to operate at night, switching off unnecessary TV sets and making small elastic economies on heating during critical winter periods, will provide much more flexibility and security of supply, at a much cheaper price, than mass capacity or storage solutions.

Crucially, passing on real-time electricity pricing to customers closes the feedback loop between available supply and customer demand. By receiving constant pricing signals, customers are encouraged to make efficiency improvements and to save energy. Most importantly, the incentive to save energy is greatest when it is most required – when supply is short. At time of excess supply, customers are able to make use of cheap power. Implementation of a demand response programme across the UK will make us aware of the true value and cost of energy. This is a key social requirement as global energy supply is changing in the new millennium.

6.1 Further work

During the course of this work, several areas of further research have been identified. The most important such areas are outlined here:-

- Forecasting models. Demand and price forecasting models need to be refined. The demand and price forecasting model needs to account for the anticipated effect of a price change on the subsequent electrical demand. The forecasting algorithm used in this report did not account for short-term demand change as a direct result of price change, and the result was inadequate feedback leading to oscillations and system instability. The forecasting model needs to avoid this situation, while still allowing rapid responses to unexpected changes in demand. The requirements on this algorithm are therefore quite severe and much more research is needed. The effectiveness of the forecasting algorithm affects the allowed automated domestic response load/storage powers and the interaction between these needs to be better understood.
- Better algorithms are required for automated customer load shifting, both in real life and within the simulation tool. The modifications are required to avoid all households shifting loads to the same, cheapest forecast time and therefore turning demand “valleys” into demand peaks. The problem here is to find ways of automatic domestic response via each house’s programmable price panel, which still maintaining enough diversity between houses.
- The simulation model presented here assumes that all houses are homogeneous – i.e. all houses are the same size, and have essentially random but uncorrelated attributes of hardware and behaviour. In reality, houses will have different incomes, behaviour and load profiles. It would be beneficial to understand this and to model the effects. Doing so is challenging, however, and finding appropriate hard social data in a suitable form might be impossible. The homogeneous approach might be the only viable solution.
- The simulation presented here assumes that houses buy and sell power at the same price. This is unlikely to be an option in reality. More likely a fair sale price of electricity from a household, at times of net energy export, would be the buy price minus 2x the DUoS figure. It would be useful to expand the software model to account for net export revenues at this lower price. This would be a relatively easy task in itself; however, it complicates the cost-benefit calculations for storage and renewable generation installation, since domestic net export quantities do not equal the dis-aggregated exports from each individual export type. This is because much domestic energy generation or release is not exported at the sale price but instead offsets purchased power.
- More analysis is needed to fully understand the optimum economic patterns for buying and selling of stored energy, and how this affects network stability and customer revenues.

7 Appendix

7.1 Glossary

AM	Advanced meter, or Advanced Metering
DR	Demand Response
BM	Balancing Mechanism
Brown	Brown appliances include such things as TV’s, radios, hifi, computers etc.
BSC	Balancing and Settlement Code
BSP	Bulk Supply Point. Node at which the transmission network meets a distribution network.
BSUoS	Balanced Services Use of System charge
Cold	Cold appliances include such things as fridges, freezers etc.
CCGT	Combined-Cycle Gas Turbine
CSP	Curtailment Service Provider
DNO	Distribution Network Operator
DR	Demand Response
DRM	Distribution Reinforcement Model
DTI	Department of Trade and Industry
DUoS	Distributed Use of System charge
EHV	Extra-High Voltage. Generally, anything above 400kV. Not currently in use in the UK, but 735kV is used for long distance bulk power transmission in the USA.
GSP	Grid Supply Point. A point in the transmission grid where a large generator or load centre is attached.
HV	High Voltage, 66kV, 132kV, 275kV and 400kV in the UK
JRC	Joint Radio Company
Load Factor	An expression of the average power output of an electrical generator relative to its peak generation capacity. If a wind turbine has a peak capacity of 1MW but only generates an average of 0.3MW year-round due to wind conditions, maintenance outages or inability to sell its power, then it’s load factor is 0.3/1=30%. Load Factor can also apply to an electrical demand in the same way. Load Factors closer to 100% imply steady generation or consumption. Lower Load Factors imply more peaky or spiky generation or demand. A generator with a low Load Factor can be hard to operate financially since capital costs must be recovered from small energy sales relative to the installed capacity of the plant.
LV	Low Voltage. In the UK: 230V (single phase) and 415V (three phase)
MV	Medium Voltage. In the UK: 6.6kV, 11kV, and 33kV in the UK
NGC	National Grid Company
Ofgem	Office of gas and electricity markets
PV	Photovoltaic

REC	Regional Electricity Company; a competitor to the DNO, providing a service and financial package wrapper to the DNO service. They do not provide the actual network connectivity which is still the responsibility of the DNO.
RPI	Relative Price Index. The forecast electricity price divided by the customers perception of the average electricity price (determined by a weighted average over a number of previous days)
RPI-X	Price control applied by Ofgem to electricity for annual rises. Retail price index (RPI) minus expected network efficiency gains (X).
RSI	Residual Supply Index, determined on a half-hourly basis and if less than 1, the power seller is pivotal and a bid must be accepted.
SEPA	Scottish Environment Protection Agency
SMA	Supply Margin Assessment. Similar to RSI but done on a daily peak demand basis.
SMES	Superconducting Magnetic Energy Storage
TOU	Time Of Use (charging for electricity)
TNUoS	Transmission Network Use of System charge
Wet	Wet appliances include such things as washing machines, tumble dryers, and dishwashers

7.2 Potential future renewable UK energy sources

7.2.1 Potential UK biodiesel production from intensive crop farming

- Mean UK insolation at sea level ~100Wm^{-2} over 24 hours, 365 days per year [6].
- Intensive biomass crops in temperate climate can transform ~1.6% of this into raw fuel calorific value. (Biodiesel after processing ~0.14%).
- Hypothetically, assume 10% of UK landmass set aside for Biomass crops (10% of 22982700 ha = 2.298E10m^2 [6]):-
- Annual raw energy fuel output = 365*24*2.298E10*100*(0.016 or 0.0014)
- = ~320TWh @ 1.6% conversion efficiency (solid fuel theoretical maximum)
- = ~12GW @ 1.6%*33% conversion efficiency to electricity
- = ~28TWh @ 0.14% conversion efficiency (biodiesel)
- Current UK transport energy use ~= 400TWh [11]
- 28/400 = 7%, leaving 93% of transport requirements remaining to be curtailed or fulfilled from other energy sources.

7.2.2 Potential UK domestic PV electricity production

- In 2001 there were approximately 25 million households in the UK (DTI [8]).
- Some of these will be houses and some will be flats
- Assuming that each household on average could install a 2x2 metre array, i.e. 4 m^2.
- Mean UK insolation at sea level ~100Wm^{-2} over 24 hours, 365 days per year [6].
- Peak UK insolation at sea level is approximately 500-1000W/m^2 (estimated as half the peak insolation at the equator which is ~=1kW/m^2). The panels are rated for insolations of 1000W/m^2.
- Efficiency of a PV system assumed to be 15%. The 4m^2 array would be rated at 4*1000*0.15=600W peak.
- Agregate UK energy production ~= 25E6*4*100*24*365*0.15 ~= 13TWh/a
- Peak UK energy production, assuming a hypothetically clear sunny day over the whole UK, might be approximately 25E6*4*500*0.15 = 7.5GW
- This could double to 15GW (26TWh/a) if houses installed 8m^2 arrays (800W peak systems), or rise to 30GW (52TWh/a) for 16m^2 arrays (2.4kW peak).
- The load factor for grid-connected PV electrical production in the UK is approximately 100W/500W=20% or less

7.2.3 Potential UK solar water heater energy capture

- In 2001 there were approximately 25 million households in the UK (DTI [8]).
- Some of these will be houses and some will be flats
- Assuming that each household on average could install a 2x2 metre collector, i.e. 4 m^2.
- Mean UK insolation at sea level ~100Wm^{-2} over 24 hours, 365 days per year [6].

- Peak UK insolation at sea level is approximately 500-1000W/m^2 (estimated as half the peak insolation at the equator which is ~=1kW/m^2)
- Peak output of a 4 m^2 at 1000W/m^2 is about 2.5kW, by using the design tool referred to in section 4.9.3.
- Therefore, efficiency of a thermal collector system is approximately 60%.
- Agregate UK energy production ~= 25E6*4*100*24*365*0.6 ~= 53TWh/a
- Peak UK energy production, assuming a hypothetically clear sunny day over the whole UK, 25E6*4*500*0.6 = 30GW
- This figure could rise to 60GW for 8m^2 (5kW peak) systems.

7.2.4 Potential UK land-based windpower production

We could estimate the peak land-based windpower, very basically, by imagining, say, 4 lines of 1MW wind turbines stretched from the North to South of the UK. The spacing would be approximately 100M and the distance is about 1000kM. This means a peak capacity of 4*1000*1000/100 * 1MW = 40000 * 1MW = 40GW. We could attain more peak capacity but space and planning permission are big issues. The load factor would be around 30%.

7.2.5 Potential UK offshore windpower production

Offshore, we could presumably realise amounts of wind power of about 40GW also, probably by using fewer but larger capacity turbines. The load factor would probably be a little better, say 40%, due to the more consistent maritime wind conditions. Access to shipping routes is a factor which would make such large-scale deployment difficult.

7.2.6 Potential UK wave power production

We could imagine a line of Pelamis wave converters stretching the length of the western coast of the UK. Assuming each wave machine peak power output rises from the current 750kW to something more like 1MW, and the machines could be spaced as per the Pelamis recommended configuration of 40 machines per km^2 (each km^2 is actually 2.1km long by 600m deep). The total theoretical peak capacity is then 1000km/2.1*40 * 1MW = 19 GW. The load factor would probably remain at about 40% (current Pelamis published data). Access to shipping routes is a factor which would make such large-scale deployment difficult.

7.2.7 Potential UK tidal power generation

We might imagine 100 suitable sites around UK coastal waters that might support a 1MW tidal flow stream converter. These sites are extremely limited by suitable tidal flow, environmental considerations and operational difficulties. Peak capacity might be 100MW. Load factor will be reasonable and predictable, say 50%.

7.2.8 Potential UK anaerobic digestion of domestic organic waste to biogas production

Analysis using an anaerobic digestion tool developed by the “Biomass group” [5] at Strathclyde university shows that the electrical power realisable by processing the domestic organic waste from a population of 60 million people would be between 130 and 330MW. The energy release would to some extent be controllable as the biogas could be stored in a similar fashion to our current natural gas reservoirs. The load factor would be limited mainly by the reliability of fuel supply and the availability of the demand market, as opposed to climactic factors.

7.2.9 Potential UK wood to energy production

Analysis in [5] reveals that *Substantial areas of forest are needed to support a wood-fired power station. For example, a 6MW station with an efficiency of 20% would need between 430 and 2,150 hectares a year of sustainably managed forest at harvest. This exceptionally wide range shows the variable yield of forest residues. The yield itself depends on various factors such as terrain, accessibility, tree species and age, and end use of the timber - as opposed to the residues - will be put. However, the feasibility of this will also depend on other issues, such as the conservation status of the woodland, accessibility and countryside policies.*

In Scotland there are over 1,318,000 hectares of woodland and forest, so this would equate to 6MW*1318000/430=18GW to 6MW*1318000/2150=3.6GW. We could double these figures to estimate total UK wood reserves. Comparison with section 7.2.1 would suggest that 10% of all UK landmass used intensively (2,298,270ha) would only support 12GW of electrical generation. A fair estimate for peak UK capacity would seem to be about 10GW. Environmental impact and fuel transport issues will limit any successful bulk implementation. The load factor could be both controllable and reasonable.

7.3 Storage technologies

7.3.1 Batteries

Deep-cycle lead-acid batteries are the most common form of electrical storage device aside from pumped storage. The scales are quite different, however, since the cost of lead-acid batteries has not traditionally made them feasible for bulk storage on the network, or domestic-scale storage at home.

A deep-cycle lead-acid battery, measuring 0.28m x 0.18m x 0.19m and weighing 20kg [13] can have a declared storage capacity of 100Ah @ 12V, at a cost of £87+VAT. The realisable capacity of this battery might be 70% x 100 x 12 = 0.84 kWh, and it might be available for about £50 purchased in bulk quantities.

In reality, storing the energy will require passing through AC-DC converters, the battery, and DC-AC inverters. The efficiency of the converters might be 97-98% each, and the batteries might be 90% efficient at best. Therefore, each battery might require 0.84/0.97/0.9 = 0.96 kWh to charge, and might only release 0.84 x 0.97 = 0.81 kWh.

Therefore, one household, on average, with a 12.6kW/day usage, could in theory store 1 day's worth of electrical energy in approximately 12.6/0.81 ~= 16 batteries, at a cost of £800 plus the cost of the inverters. To store enough for a 5 or 10 day weather event, each household on average would need between 80 to 160 batteries, with a combined mass of 3200kg and requiring the space of a small shed 2.5m x 1.5m x 1.5m, assuming that only 1/3 of the volume can be used for the batteries and 2/3 must be saved for access and maintenance requirements. The cost would be £4000-£8000 plus the cost of the inverters. It is technically feasible, but bulky and expensive. The batteries also have a finite lifetime and require a level of maintenance.

At an electricity cost of 7p/kWh and an average household consumption of 12.6kW/day (4600kWh/annum), the average household electricity bill is currently £322 per year. Unsurprisingly, an investment of £4000-8000 per household for this kind of storage facility, representing over 10 times an annual electricity bill, is unappealing. Few people have this kind of system apart from those without grid connections, or those with a "personal mission" to prove the feasibility of embedded renewables[4].

[4] The incentive for these people to install domestic storage is that current grid connection of domestic renewables provides vastly different (but fixed) rates for import and export. The export rate paid to the user is very low (below the lowest wholesale price). Therefore, these people currently justify their investment in battery storage because it makes them almost self-sufficient from the grid, so that they do not get punished by the imbalanced import and export rates.

However, if domestic electricity prices were to move to a more real-time basis, following the wholesale market prices, there might be real financial justification for normal users.

If a 160-battery micro-storage facility was built as described above for a cost of £8000 (plus inverters), in a domestic or embedded manner, the following scenario might occur:-
Overnight, 160 x 0.96 = 153.6 kWh might be purchased at £25/MWh (in the distribution network), at a total cost of £3.84.
During a following day, 160 x 0.81 = 129.6 kWh might be sold at peak rates of £50/MWh (in the distribution network), for a revenue of £6.48.
The revenue minus expenses for the day might be £2.64. Over a year, this could amount to about £960. Over 10-15 years, dependent upon interest rates, the capital sum of £8000 (plus converters) might be paid off, although the system will be requiring maintenance and possibly battery replacements by then.

This system is marginally feasible according to this rather over-simplified analysis, although not obviously profitable enough (at present) to justify investment. However, a doubling or trebling in overall wholesale energy prices, or an increase in peak price electricity, might easily make the system much more appealing from a financial viewpoint.

Technically, the system is quite feasible, although large proportions of UK households in the UK were to consider the scheme, one might question the space requirements, the chemical spill hazard, the maintenance required, and the physical amount of lead required and the impact on the worldwide lead market. Possibly, the global supply of lead might limit such a scheme! An alternative option is an electrolyte store which would store large amounts of electrolyte but only use a few lead plates. This limits the instantaneous power available, but, as we shall see later in this report, this does not present a problem for embedded storage due to stability requirements.

As a comparison of energy storage density, we can consider the 10m x 10m x 10m cube full of batteries (at 1/3 battery-space ratio for maintenance requirements):-
Number of batteries = 10m x 10m x 10m / 3*(0.28m x 0.18m x 0.19m) = 35000
Storage capacity = 35000 x 0.81kWh = 28 MWh

7.3.2 Heated water

Heating water represents an effective method of storing energy, as the specific heat capacity of the water is so high. However, hot water is not a very good storage medium to be used for an electricity -> hot water -> electricity storage cycle. The hot water is a reasonably low grade energy which cannot readily be converted to electricity unless it is elevated to superheated temperatures and pressures. These temperatures and pressures require very strong vessels which are impractical and uneconomic to build. Large vessels of even un-pressurised water at temperature require both insulation and structural integrity.

Electricity can be used, at 100% efficiency, to heat a tank of water.

In a 10m x 10m x 10m tank, with water elevated to 90°C, relative to a base temperature of 5°C, the stored energy would be:-

$E = \text{Volume} \times \rho \times \Delta T \times c_p$

$\rho=1000\ kg/m^3$

$c_p=4.17\ kJ/kgK$

$E = 10 \times 10 \times 10 \times 1000 \times (90-5) \times 4170\ J = 354.45\ GJ \ \sim= 98\ MWh$

This equates to 98000/12.6 = 7800 household-days of electrical energy consumption.

Assuming that the tank is insulated with a 100mm (0.1m) thickness of insulation (k=0.04W/mK), the heat loss to surroundings at 5°C (with the water at 90°C) would be

$Q = \text{Area} \times \Delta T / \text{Thickness} \times k$

$Q = 6 \times 10 \times 10 \times (90-5) / 0.1 \times 0.04 = 20.4\ kW$

Hence the water would be cooling at approximately the following rate

$20400 / (10 \times 10 \times 10 \times 1000 \times 4170) \times 3600 = 0.018\ °C/hour$

and therefore the water would retain almost all the energy for at least a week (temperature drop 3°C in one week, corresponding to a 3/(90-5) = 3.5% round-trip efficiency loss).

This tank needs can be insulated well enough so as not to lose much of the heat in the time of storage required. The heat could not effectively be re-transformed into electricity unless the water was heated further and superheated by some other energy source, at which point it could be used in a steam turbine.

The water could directly be used, at high efficiency, for nearby domestic, commercial or industrial heating use.

On a smaller, domestic scale, a 120 litre immersion tank, suitable for a 1-bedroom dwelling, that heats water from an input water temperature of 8°C to 65°C, consumes and effectively stores an amount of energy:-

$E = 0.120 \times 1000 \times (65-8) \times 4170 = 28.5\ MJ \qquad \sim= 7.9\ kWh$

Heating the water, in a normal domestic immersion heater with a 3kW rating, would take 2.6 hours.

The heat loss from the tank (of diameter D=0.412 and height H=0.9m) with a 2cm thickness of insulation (k=0.04W/mK) to ambient indoors air at 20°C would be:-

$Q = \text{Area} \times \Delta T / \text{Thickness} \times k$

$Q = (2.\pi.(D/2)^2 + \pi.D.H) \times (85-20) / 0.02 \times 0.04 = 186\ W$

Hence the water would be cooling at approximately the following rate

186 / (0.120 x 1000 x 4170) x 3600 = 1.3 °C/hour = 32 °C/day (~=50% efficiency loss)
Therefore, this size of energy store will only last a day or so without excessive efficiency loss. However, in winter and poor-weather conditions, it must be borne in mind that the heat lost through the tank walls will be transmitted to the internal building environment and will displace other space-heating required, so the heat will not be wasted completely (it makes a warm airing cupboard in the centre of the dwelling!).

The stored energy of 7.9kWh (and more for proportionately larger scale tanks in larger dwellings), presents a reasonably large energy store relative to the current average household electricity consumption per day which is approximately 12.6kW/day based on a UK domestic annual usage of 115TWh and 25 million UK households [8]. Although the energy cannot reasonably be reconverted to electricity, if it can be stored without excessive heat loss and then subsequently usefully used for bathing or washing (thereby displacing later energy use, possibly at peak times) then it represents a practical and cheap method of energy storage.

7.3.3 Hydrogen

Hydrogen provides a method of storing and retrieving electrical energy via electrolysis of water and then (popularly) via use in a fuel cell. Combustion in a CCGT might be an alternative and simpler method for electrical recovery, with approximately the same conversion efficiencies when used in medium-sized or large plants.

The benefits of hydrogen storage are the (potential) energy density of the hydrogen if stored as a liquid or compressed gas, and also its transportability. The problems are the safety concerns (explosions!), the cost, and the relative immaturity of the technology. The round-trip efficiency of electrolysis -> H_2 store -> fuelcell storage cycles are currently 40% at best [3].

> *When used with a fuel cell, hydrogen and oxygen will produce perfectly clean steam and electricity with NO additional pollutants. Generally, the steam would be recycled back to the electrolysis phase after first passing through a heat exchanger and/or condensing turbines to recapture all the thermal energy. Nearly 5 MWh of electricity are required to make 1000 cubic meter of hydrogen gas (and about 500 cubic meter of oxygen). When passed through a fuel cell, this hydrogen will yield 1 MWh as electricity and 1 MWh as heat, giving an overall storage efficiency of 40%.*

Using the above data, and a molar mass of Hydrogen gas (H_2) of 2g/mole, this means that 5MWh of electricity create 1000/0.0224*2/1000=89.29kg of H_2, because 1 mole of gas occupies 0.0224m^3 at standard temperature and pressure (25°C, 1 bar). The 89.29kg of hydrogen must have been formed from 89.29 x (2+16) / 2 = 803.6 kg of water (H_2O has a molar mass of 2+16=18g). The 803.6kg of water represents 803.6/18x1000 = 44645 moles of H_20. The enthalpy change of formation of water, ΔH_F, is -285.8 kJ/mol, so the total energy that has been stored in the Hydrogen is 285.8 x 1000 x 44645 = 12.76 GJ ~= 3.54 MWh. Therefore, the efficiency of the electrolysis process, as described, is approximately 70%.

The 3.54 MWh of available stored energy translates to 1MWh electricity and 1MWh heat from the fuel cell. The electrical retrieval efficiency is therefore 28%, and the heat recovery process also recovers the same amount. The overall round-trip electrical efficiency is about 20%, and the overall round-trip recovery of heat from electricity is about 20% also.

Hydrogen might be stored in three ways:-

- In a chemical form inside a solid catalytic carrier (for transport usage since it will be safer during a collision). Currently undemonstrated on any practical scale.
- In gaseous form at high pressure (up to 3000 bar), which requires very strong storage vessels, impractical at any large scale.
- In liquid form at less than 20K.

In liquid form, the hydrogen has a density of 71kg/m^3. Therefore a 10m x 10m x 10m tank of liquid hydrogen would hold 71,000 kg of hydrogen. Using the figures above, this would require 4.0GWh of electricity to form, and would release 800MWh of electricity and 800MWh of heat when processed in the fuel cell. It is assumed that heat exchangers would minimise heating and cooling requirements associated with the hydrogen liquidisation, and that the tank would be suitable insulated.

7.3.4 Flywheels

The energy stored in a flywheel is given by :-

$E = \frac{1}{2} J\omega^2$ where J is the moment of inertia, and ω is the angular velocity in radians/second.

J is mr^2 where m is a mass at a distance r from the axis of rotation. For complex shapes,

$J = \sum_i m_i r_i^2$ which can be evaluated by integration if necessary.

If the flywheel is solid, the momentum will be

$$J = \int_0^R 2.\pi.r.\rho.H.r^2.dr = \frac{1}{2}\pi.\rho.H.R^4$$

but more practically the flywheel is hollow to minimise weight

$$J = \int_{R1}^{R2} 2.\pi.r.\rho.H.r^2.dr = \frac{1}{2}\pi.\rho.H.(R2^4 - R1^4)$$

although we can make an easier approximation to J by

$J \approx \rho.V.R^2$ where V is the rim volume and R is the rim radius.

The tensile strength at the rim exterior will be approximately:-

$T \approx \rho.R^2.\omega^2$

The speed at which this flywheel might be rotated (and indeed the technical possibility of mounting such a large weight on bearings at all) is subject to constraints. These constraints are such things as:-

- Hoop stress in the flywheel
- Precession torque
- Tilt restoration tilt
- Bearing losses and strengths
- Containment vessel strength for protection in the effent of failure

Design of flywheel so that ideally any failure results in only partial and not total shredding of the wheel.

Reference [29] gives some good descriptions of these forces and the relationships between flywheel dimensions, material density and strength. To obtain the best energy storage densities per weight and space, a very light but strong material such as carbon fibre composite is required.

Consider a flywheel to fit in $1m^3$ space, having an external radius of 0.5m, internal radius of 0.375m, height 1m, density of 1100 kg/m^3, and maximum tensile stress of $350MN/m^2$ (about right for carbon fibre)

$$\omega_{\max} \approx \frac{1}{R}\sqrt{\frac{T}{\rho}} \approx 1130 \text{ ie 11,000 rpm}$$

and

$$J \approx \rho.V.R^2 \approx 70\,\text{kgm}^2 \quad \text{where} \quad V \approx 2.\pi\frac{.(0.5+0.375)}{2}(0.5-0.375) \approx 0.34\,\text{m}^3 \quad \text{and}$$

$$R \approx \frac{(0.5+0.375)}{2} \approx 0.44$$

Hence, stored energy could be about $E = \frac{1}{2}J\omega^2 \approx 45MJ \approx 12kWh$

And the flywheel itself would weigh about 375kg. The reference claims that frictional losses on a flywheel of about this size would be only 2W, leading to an energy store “half-life” of over 600 hours. This seems optimistic, so it would be safer to assume a shorter energy “half-life” in any subsequent analysis.

Reference [29] claims that prices for flywheels are about US$6000 per kWh.

7.3.5 Compressed air

Compressed air is a simple but somewhat inefficient method for storing energy. Air is compressed by a pump or turbine and stored in a pressurised container. The air is stored, and then released via a generating turbine of some kind to generate power.

The theoretical energy storage, in a 10m x 10m x 10m vessel, pressurised to 50 bar (this will be an expensive pressure vessel!), can be calculated from the thermodynamic properties of air which can be treated as a perfect gas with $c_p/c_v=\gamma=1.4$. The calculation method assumes a polytropic adiabatic compression-expansion process.

$$Work = m.c_V.(T_2 - T_1)$$

$$\frac{T_2}{T_1} = \left(\frac{p_2}{p_1}\right)^{\frac{\gamma-1}{\gamma}}$$

and

$$pv = RT$$

Using $p_1=10^5$ Nm^{-2}, $p_2=5\times10^6$ Nm^{-2}, and T_1=293K, gives T_2=896K

For air, c_v=718 J/kgK and R=287 J/kgK

Inside the vessel, $v_2 = RT_2/p_2 = 0.0514$ m^3kg^{-1}, hence in 1000m^3 at 50 bar there is 19400kg of air at 896K.

The energy put into this storage is then 19400.718.(896-293) = 8.4 GJ ~= 2.3 MWh.

The energy available, assuming the turbines are 100% efficient and that no heat is lost, will be the same amount.

The efficiency of the system will be limited by the following effects:-

- The isentropic efficiency of the compression and expansion turbines which are unlikely to be much more than 0.8 each.
- The insulation surrounding the pressure vessel, since the air inside must be maintained at a high temperature unless energy is to be lost. Re-using the calculations and insulation thicknesses from section 7.3.2 leads to an energy loss of 148kW from the tank at 896K (623°C) to surroundings at 20°C. Storing the energy for a period of an hour would lose 4.5% of the energy, for five hours about 20% of the energy, and after 24 hours the air temperature would be almost back to ambient (20°C).

If the inside air temperature dropped to ambient (20°C), then the recoverable energy would be at most:-

T_3 = 293, $v_3=v_2$

$P_3 = RT_3/v_3$ = 287.1 x 293 / 0.0514 = 1.64 x 10^6 (16 bar)

After re-expansion

T_4 = 132K (-141°C)

Work=$m.c_V.(T_3-T_4)$ = 19400.718.(293-132) = 2.2 GJ ~= 0.62 MWh

Therefore, the round trip efficiency of compressed air storage at 50 bar is at best 0.8 x 0.8 = 64%, limited by the isentropic efficiency of the turbines. At worst, after several hours if the compressed air loses its heat, the efficiency drops to 0.8 x 0.8 x (0.62/2.3) = 17%.

7.3.6 Superconductivity

The principle of energy storage using superconductivity revolves around a superconducting closed ring or coil of wire. Current flows in the wire, which has zero resistance and zero voltage between any two points. Energy is stored via the inductance of the wire or coil, via $E=\frac{1}{2}LI^2$. The energy is stored in a magnetic field created by the current. Power is injected into the ring by "injecting" current, and it extracted by "tapping" off some of the current.

The problems which limit energy storage in superconducting rings are:-

- The current stored in the ring is limited, by the "critical current" property of superconductors. Above a critical current density, the wire ceases to exhibit the property of superconductivity.
- There is also a critical magnetic field property, whereby the property of superconductivity in a wire ceases when a certain magnetic field density is exceeded.

Because of the above two limitations, a storage facility for 1000MWh would require a ring approximately 100 miles big [33].

The conductor (currently) needs to be immersed in liquid helium to maintain the superconducting property.

The magnetic fields generated by a significant energy store would dwarf the earth's latent magnetic field, and might pose health risks or other effects (compass swings, magnetic card swipes deleted, attraction of metal objects, induced currents in moving metal objects, and other annoyances).

Superconducting magnetic energy storage (SMES) has been demonstrated successfully in commercial and military applications up to 6MJ/750kVA (~= 1.5kWh) using niobium-titanium rings maintained at 4.2K [24], [1], [2] in trailer-sized packages. The major application of SMES systems is for very short-term (0 to 10 second), high current applications such as power conditioning and ride-through for transient faults and spikes (e.g. lightning strikes) at critical installations. The SMES systems can respond with 2ms or so, just a fraction of a power cycle.

Figure 7-1 2MJ, 200kVA (8 second carry-over time) SMES system

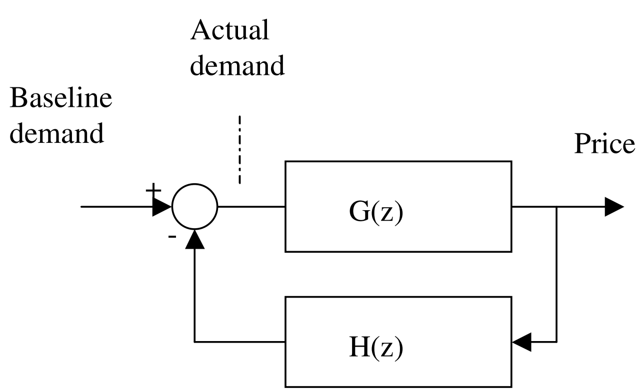
7.4 Stability of a simple demand-price control system

The problem of instability can arise in a demand response system when the (downwards) change in demand due to an (upwards) price change causes a subsequent (downwards) change in price which is larger than the original (upwards) price change. This will cause an unstable system, of which several examples have been observed when using the modelling tool. The instability can be caused by any or all of the combined effects:-

- Inadequate forecasting models
- Excessive storage power which is activated over small price change ranges. Note, there is a clear distinction here between storage power and storage energy. Large amounts of stored energy are not a problem. Instability is caused by it being absorbed or released over too small a price range.
- Excessive elasticities of demand
- Excessively steep price-demand curves

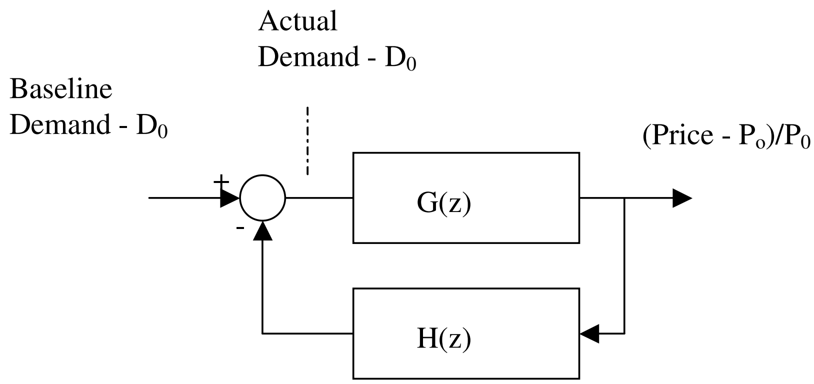
The following calculations were an attempt to put some bounds on the maximum storage powers or elasticities which might be allowed in a system. Unfortunately, the output of the calculations does not reveal this, although a very important conclusion becomes clear.

A demand-response system in which demand and price depend upon each other may be modelled, in very simplistic terms, by a classic digital control system.



In this model, G(z) is Z-transform of the demand to price equation. H(z) is a combination of the effect on demand due to price, plus the forecasting model.

Since control system theory works best with linear systems, the above diagram must be modified to be able to analyse the potential stability of the demand-response system. This is because our price-demand equation is not linear (section 4.7), and because there are large offsets from zero in the system. The modified control system models excursions from a nominal demand D_0 and price P_0, while using an approximation of the gradient of the price-demand curve at the nominal point D_0, P_0.



Here we set, at time t_0, demand D_0 and price P_0. For $t>t_0$, the system models the excursions from the starting point. Note that the output of the system is now not the absolute price excursion, but the excursion divided by the reference price P_0. This means that the output is in fact the relative price excursion, which relates to the RelPriceIndex parameter in the main demand response modelling (see sections 4.11 and 4.12.1). This is useful since demand responses are driven by price relative to the customers' perceived average, and not absolute prices.
G(z) is now the gradient of the price curve divided by P_o, i.e. it is the derivative of

$$\Pr ice = \frac{Ae^{Bx} + C + DuOS}{P_0}$$ evaluated at D_0, P_0

where $x = \dfrac{Demand}{Capacity - L\arg estGeneratorCapacity}$

G(z) is therefore $\dfrac{BAe^{Bx}}{P_0(Capacity - L\arg estGeneratorCapacity)}$

H(z) is harder to formulate. H(z) is the combination (by product) of Z-transform of the forecasting model with the Z-transform of the demand change (in Watts) as a function of relative price change.

Taking the forecasting model first, it is almost certainly impossible to derive analytically the z-transform of the forecasting function described in section 4.8, which is a combination of polynomial fitting plus fourier analysis. It will also be impossible to derive the z-transform of more professional prediction algorithms that take into account weather forecasts and TV schedules. Therefore, probably the best we can do here is to analyse a very basic, weak, forecasting model, and make the statement that whatever results we get here can almost certainly be bettered by using a decent forecasting model. We will then put a safe limit on storage power and elasticity that may be used without any danger of instability, using the most stupid of forecasting algorithms. The forecasting model we can use here is a simple this-to-next algorithm. This means that we forecast the price in the next period to be the same as it was due to the demand in the previous period. It is similar to making a weather forecast for tomorrow by saying it will probably be just like today – it often works! The z-transform for such a simple forecast is simply z^{-1} since it corresponds to data passed with a one-sample delay.

Now, we must derive the portion of H(z) due to either storage power flow or elastic change in demand.

For storage, the upward change in demand for a decrease in relative price will be approximately

$$\frac{N_H \overline{P}_S}{P_{R1Buy} - P_{R2Buy}}$$

where N_H is the number of households with storage and $\overline{P}_S$ is the average storage power flow that can be activated by each house. $P_{R1Buy} - P_{R2Buy}$ is the relative price range over which the N_H houses make their decisions to buy power. Typically, P_{R1Buy} might be 0.95 and P_{R2Buy} might be 0.5. This signifies that houses choose to buy power between these relative prices, and if N_H is large enough, the gradual increase of numbers of houses buying power as price moves downwards over this range will cause a linear change in demand. Here, we assume that the linear change extends into the range where relative price is >1 also.

The upward change in demand by elastic change in response to a decrease in relative price will be approximately $-E_0D_0$. Remember that E_0 will be negative. E_0 here is also the elasticity valid relative to the price P_0, which is not necessarily the same price as elasticities calculated relative to other prices. It will be necessary to scale E_0 to make it valid at a price other than P_0.

In summary,

So, now it is possible to combine the equations G(z) and H(z) and determine the stability of the system.

The closed-loop transfer function of the system is $\frac{G(z)}{1+G(z)H(z)}$, and the stability of the system is determined by the location of the poles of this function in z-space. The poles are determined by finding the zeros of the characteristic equation $1+G(z)H(z)$. It is useful to rewrite this equation as $1+Kg(z)$, since this separates the scalar gain factor K from the difference equation part g(z).

In our case, g(z) is simply z^{-1} while K is the product of all the other scalar factors. We can now find the sole zero of the characteristic equation, which falls at z=-K.

A digital control system is stable is the poles of the closed-loop transfer function fall within the unit circle on the complex z plane. In our case, clearly, the magnitude of K must be less than one for our simple system to be stable.

We can now apply this criteria to K and backtrack to find approximate acceptable limits on the storage power per house, or maximum elasticity, that may be allowed in conjunction with a very poor forecasting model.

We assume:-

N_H=25,000,000

Capacity=52GW, LargestSingleGenerator=2GW, =>Capacity-LargestSingleGenerator=50GW

P_0=15 pence/kWh (150£/MWh)

Hence $x = \dfrac{\ln\left(\dfrac{150 - C - DUoS}{A}\right)}{B}$, which gives 0.94 using price model parameters from the mid curve (Figure 4-13) of A=0.0001, B=15 and C=12, and DuoS of 8 £/MWh.

D_0 can be evaluated as x*50 GW = 47.0GW

We can now solve two equations, one to find the maximum storage power per average house to cause instability, and one to find the maximum elasticity to cause instability.

$$K_{Storage} < 1$$
$$K_{Elasticity} < 1$$

These two equations, when expanded, form

$$\frac{BAe^{Bx}}{P_0(Capacity - L\arg estGeneratorCapacity)}\left[\frac{N_H \overline{P}_S}{P_{R1Buy} - P_{R2Buy}}\right] < 1$$
$$\frac{BAe^{Bx}}{P_0(Capacity - L\arg estGeneratorCapacity)}\left[-E_0 D_0\right] < 1$$

which can be evaluated as

$$\frac{15*0.0001e^{15*0.93}}{150(50*10^9)}\left[\frac{25*10^6\overline{P}_S}{0.95-0.5}\right]<1$$

$$\frac{15*0.0001e^{15*0.93}}{150(50*10^9)}\left[-E_0*46.5*10^9\right]<1$$

then

$$\frac{13.0}{50*10^9}\left[\frac{25*10^6\overline{P}_S}{0.95-0.5}\right]<1$$

$$\frac{13.0}{50*10^9}\left[-E_0*47.0*10^9\right]<1$$

Hence

$\overline{P}_S$ < 70 Watts

$-E_0 < 0.08$

These are disappointingly small figures. Considering that each house may well have an immersion element of at least 3000W alone, plus potentially other electrical storage, there is no way that the system can be stable. We would also hope that overall household elasticity of demand might reach the order of -0.2 to -0.5, which is a substantially higher elasticity than -0.08.

The conclusion here is simple. **It is almost impossible to guarantee absolute system stability from a theoretical standpoint with a simple analysis such as this. The forecasting models used in reality, for a demand response system, must be orders of magnitude better than a simple estimate based upon the demand and price from the single previous period**. The forecasting model used in the demand response model described in section 4.8 must be much better than the worst-case forecasting method, because successful simulations can be demonstrated using much higher storage powers per house than 77W. But it is almost certainly possible to determine the z-transform of the current forecasting model or any reasonable candidate algorithms, aside from some very simple approximations based upon low-pass filters. Therefore, system stability will probably have to be determined by empirical (trial and error) methods. For this, the demand response simulation software which incorporates the candidate forecasting algorithm will therefore be invaluable.

7.5 Derivation of solar view angles & solar panel rotations

The following algorithm finds the angles of the sun for a given location on the planet and time, and computes these angles relative to a solar panel orientation. The collectable "power factor" of the solar collector relative to the total direct normal solar irradiance available is calculated.

Inputs:-
Latitude, Longitude
Time (in GMT, relative to midday on 21 June - at time t=0 a point at longitude 0 in the N hemisphere has it's highest sun angle possible)
Azimuth (towards East) and declination rotation offsets for the solar panel from nominal flat.
Outputs:-
Solar declination, in degrees from directly overhead
Solar bearing, a compass bearing of the sun position relative to true North
The AimFactor power, which is the power available relative to direct normal solar
The bearing, declination, and overall angle errors of the panel orientation

The earth centre is considered stationary at [0,0,0] with the sun stationary at [infinity,0,0]
We begin by considering the point closest to the sun at t=0, on the equator.This is a vector of [1,0,0].
This vector towards the sun points directly overhead in a direction of [1,0,0].
We also know that views East and North from this point at this time are [0,1,0] and [0,0,1] respectively.
Know we apply the following rotations in order, to find these three vector directions for the correct location and time:-
Rotation of latitude
Rotation of longitude
Rotation due to rotation of earth about N-S (the z) axis (every 23 hours 56 minutes)
Rotation of the N-S axis of earth about the y axis (23.45 degrees off axis)
Rotation earth and its N-S axis about the z axis every 365.25 days

The three transformed (overhead, East and West view) vectors for are now compared to the sun-view vector which remains [1,0,0]

The three vectors EastVector, NorthVector and OverheadPointer form a right-handed orthogonal set of axes.
We use these three vectors to form the actual panel pointer vector, by using a rotation towards East and a declination from overhead.
This is an azimuth-declination transform similar to radar antenna pointing.

```
> restart;
> RzAnnual:=linalg[matrix](3,3,[[cos(epsilon),-
sin(epsilon),0],[sin(epsilon),cos(epsilon),0],[0,0,1]]);
```

$$RzAnnual := \begin{bmatrix} \cos(\varepsilon) & -\sin(\varepsilon) & 0 \\ \sin(\varepsilon) & \cos(\varepsilon) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

```
>
RyAxisOffset:=linalg[matrix](3,3,[[cos(phi),0,sin(phi)],[0,1,0
],[-sin(phi),0,cos(phi)]]);
```

$$RyAxisOffset := \begin{bmatrix} \cos(\phi) & 0 & \sin(\phi) \\ 0 & 1 & 0 \\ -\sin(\phi) & 0 & \cos(\phi) \end{bmatrix}$$

```
> RzDaily:=linalg[matrix](3,3,[[cos(theta),-
sin(theta),0],[sin(theta),cos(theta),0],[0,0,1]]);
```

$$RzDaily := \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

```
> RzLongitude:=linalg[matrix](3,3,[[cos(alpha),-
sin(alpha),0],[sin(alpha),cos(alpha),0],[0,0,1]]);
```

$$RzLongitude := \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0 \\ \sin(\alpha) & \cos(\alpha) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

```
>
RyLatitude:=linalg[matrix](3,3,[[cos(beta),0,sin(beta)],[0,1,0
],[-sin(beta),0,cos(beta)]]);
```

$$RyLatitude := \begin{bmatrix} \cos(\beta) & 0 & \sin(\beta) \\ 0 & 1 & 0 \\ -\sin(\beta) & 0 & \cos(\beta) \end{bmatrix}$$

```
>
OverheadRotationCombo:=linalg[multiply](RzAnnual,RyAxisOffset,
RzDaily,RzLongitude,RyLatitude);
```

$OverheadRotationCombo :=$

$$\begin{aligned}
&[((\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha) \\
&+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta) \\
&- \cos(\varepsilon)\sin(\phi)\sin(\beta), -(\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\sin(\alpha) \\
&+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\cos(\alpha), (\\
&(\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha) \\
&+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta) \\
&+ \cos(\varepsilon)\sin(\phi)\cos(\beta)] \\
&[((\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha) \\
&+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta) \\
&- \sin(\varepsilon)\sin(\phi)\sin(\beta), -(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\sin(\alpha) \\
&+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\cos(\alpha), (\\
&(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha) \\
&+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta) \\
&+ \sin(\varepsilon)\sin(\phi)\cos(\beta)] \\
&[(-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\cos(\beta) - \cos(\phi)\sin(\beta), \\
&\sin(\phi)\cos(\theta)\sin(\alpha) + \sin(\phi)\sin(\theta)\cos(\alpha), \\
&(-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\sin(\beta) + \cos(\phi)\cos(\beta)]
\end{aligned}$$

```
>
OverheadPointer:=linalg[multiply](OverheadRotationCombo,linalg
[vector]([1,0,0]));
```

$OverheadPointer := [((\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta)$
$- \cos(\varepsilon)\sin(\phi)\sin(\beta), ((\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta)$
$- \sin(\varepsilon)\sin(\phi)\sin(\beta),$
$(-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\cos(\beta) - \cos(\phi)\sin(\beta)]$

```
> NorthVector:=linalg[multiply](OverheadRotationCombo,linalg[vector]([0,0,1]));
```

$NorthVector := [((\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta)$
$+ \cos(\varepsilon)\sin(\phi)\cos(\beta), ((\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta)$
$+ \sin(\varepsilon)\sin(\phi)\cos(\beta),$
$(-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\sin(\beta) + \cos(\phi)\cos(\beta)]$

```
> EastVector:=linalg[multiply](OverheadRotationCombo,linalg[vector]([0,1,0]));
```

$EastVector := [-(\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\sin(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\cos(\alpha),$
$-(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\sin(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\cos(\alpha),$
$\sin(\phi)\cos(\theta)\sin(\alpha) + \sin(\phi)\sin(\theta)\cos(\alpha)]$

```
> PanelPointer:=evalm(linalg[scalarmul](OverheadPointer,cos(SPD))+linalg[scalarmul](EastVector,sin(SPD)*sin(SRE))-linalg[scalarmul](NorthVector,sin(SPD)*cos(SRE)));
```

$PanelPointer := [\cos(SPD)(((\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta)$
$- \cos(\varepsilon)\sin(\phi)\sin(\beta)) + \sin(SPD)\sin(SRE)($
$-(\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\sin(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\cos(\alpha)) - \sin(SPD)\cos(SRE)(($
$(\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta)$
$+ \cos(\varepsilon)\sin(\phi)\cos(\beta)), \cos(SPD)(($
$(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta)$

$- \sin(\varepsilon)\sin(\phi)\sin(\beta)) + \sin(SPD)\sin(SRE)($
$-(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\sin(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\cos(\alpha)) - \sin(SPD)\cos(SRE)(($
$(\sin(\varepsilon)\cos(\phi)\cos(\theta) + \cos(\varepsilon)\sin(\theta))\cos(\alpha)$
$+ (-\sin(\varepsilon)\cos(\phi)\sin(\theta) + \cos(\varepsilon)\cos(\theta))\sin(\alpha))\sin(\beta)$
$+ \sin(\varepsilon)\sin(\phi)\cos(\beta)), \cos(SPD)$
$((-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\cos(\beta) - \cos(\phi)\sin(\beta))$
$+ \sin(SPD)\sin(SRE)(\sin(\phi)\cos(\theta)\sin(\alpha) + \sin(\phi)\sin(\theta)\cos(\alpha)) -$
$\sin(SPD)\cos(SRE)$
$((-\sin(\phi)\cos(\theta)\cos(\alpha) + \sin(\phi)\sin(\theta)\sin(\alpha))\sin(\beta) + \cos(\phi)\cos(\beta))]$

```
> SunDeclinationFromOverhead_F:=arccos(OverheadPointer[1])*180/Pi;
```

$$SunDeclinationFromOverhead\_F := 180 \arccos(((\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\varepsilon)\sin(\theta))\cos(\alpha) + (-\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\varepsilon)\cos(\theta))\sin(\alpha))\cos(\beta) - \cos(\varepsilon)\sin(\phi)\sin(\beta))/\pi$$

```
> North:=linalg[dotprod](NorthVector,linalg[vector]([1,0,0]));
```

$$North := \sin(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) - \sin(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) + \cos(\varepsilon)\sin(\phi)\cos(\beta)$$

```
> East:=linalg[dotprod](EastVector,linalg[vector]([1,0,0]));
```

$$East := -\sin(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) + \sin(\alpha)\sin(\varepsilon)\sin(\theta) - \cos(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) - \cos(\alpha)\sin(\varepsilon)\cos(\theta)$$

```
> SunBearing:=arctan(East,North)*180/Pi;
```

$$SunBearing := 180 \arctan(-\sin(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) + \sin(\alpha)\sin(\varepsilon)\sin(\theta) - \cos(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) - \cos(\alpha)\sin(\varepsilon)\cos(\theta), \sin(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) - \sin(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) - \sin(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) - \sin(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) + \cos(\varepsilon)\sin(\phi)\cos(\beta))/\pi$$

```
> AimFactor:=evalm(linalg[dotprod](PanelPointer,linalg[vector]([1,0,0])));
```

$$
\begin{aligned}
AimFactor :=\ & \cos(SPD)\cos(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& - \cos(SPD)\cos(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) \\
& - \cos(SPD)\cos(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& - \cos(SPD)\cos(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) - \cos(SPD)\cos(\varepsilon)\sin(\phi)\sin(\beta) \\
& - \sin(SPD)\sin(SRE)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& + \sin(SPD)\sin(SRE)\sin(\alpha)\sin(\varepsilon)\sin(\theta) \\
& - \sin(SPD)\sin(SRE)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& - \sin(SPD)\sin(SRE)\cos(\alpha)\sin(\varepsilon)\cos(\theta) \\
& - \sin(SPD)\cos(SRE)\sin(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& + \sin(SPD)\cos(SRE)\sin(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) \\
& + \sin(SPD)\cos(SRE)\sin(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& + \sin(SPD)\cos(SRE)\sin(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) \\
& - \sin(SPD)\cos(SRE)\cos(\varepsilon)\sin(\phi)\cos(\beta)
\end{aligned}
$$

```
> SunOffsetFromPanelDegs_F:=arccos(AimFactor)*180/Pi;
```

$$
\begin{aligned}
SunOffsetFromPanelDegs\_F :=\ & 180\,(\pi - \arccos(\\
& -\cos(SPD)\cos(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& + \cos(SPD)\cos(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) \\
& + \cos(SPD)\cos(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& + \cos(SPD)\cos(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) + \cos(SPD)\cos(\varepsilon)\sin(\phi)\sin(\beta) \\
& + \sin(SPD)\sin(SRE)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& - \sin(SPD)\sin(SRE)\sin(\alpha)\sin(\varepsilon)\sin(\theta) \\
& + \sin(SPD)\sin(SRE)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& + \sin(SPD)\sin(SRE)\cos(\alpha)\sin(\varepsilon)\cos(\theta) \\
& + \sin(SPD)\cos(SRE)\sin(\beta)\cos(\alpha)\cos(\varepsilon)\cos(\phi)\cos(\theta) \\
& - \sin(SPD)\cos(SRE)\sin(\beta)\cos(\alpha)\sin(\varepsilon)\sin(\theta) \\
& - \sin(SPD)\cos(SRE)\sin(\beta)\sin(\alpha)\cos(\varepsilon)\cos(\phi)\sin(\theta) \\
& - \sin(SPD)\cos(SRE)\sin(\beta)\sin(\alpha)\sin(\varepsilon)\cos(\theta) \\
& + \sin(SPD)\cos(SRE)\cos(\varepsilon)\sin(\phi)\cos(\beta)))/\pi
\end{aligned}
$$

```
> DPE_F:=evalm(linalg[dotprod](PanelPointer,EastVector));

> DPN_F:=evalm(linalg[dotprod](PanelPointer,NorthVector));

> PanelBearing:=arctan(DPE,DPN)*180/Pi;
```

$$PanelBearing := 180\,\frac{\arctan(DPE, DPN)}{\pi}$$

```
>
PanelDeclination_F:=arccos(evalm(linalg[dotprod](PanelPointer,
OverheadPointer)))*180/Pi;
```

Above are all the big formulas. Below we put the numbers in

```
phi:=23.45*Pi/180;
```

$$\phi := .1302777778\ \pi$$

```
> LongEastDegs:=-3.169; LatNDegs:=55.977;
```

$$LongEastDegs := -3.169$$

$$LatNDegs := 55.977$$

```
> SolarPanelRotationToEast:=0; SolarPanelDeclination:=30;
```

$$SolarPanelRotationToEast := 0$$

$$SolarPanelDeclination := 30$$

```
> Date:=242.5;
```

$$Date := 242.5$$

t is time (in days) relative to midday (GMT) on June 21 of a reference year when Greenwich obtains it's most overhead sun possible at this time.

```
> t:=(Date-171.5);
```

$$t := 71.0$$

```
> alpha:=LongEastDegs*Pi/180;
```

$$\alpha := -.01760555556\ \pi$$

```
> beta:=-LatNDegs*Pi/180;
```

$$\beta := -.3109833333\ \pi$$

```
> SRE:=SolarPanelRotationToEast*Pi/180;
SPD:=SolarPanelDeclination*Pi/180;
```

$$SRE := 0$$

$$SPD := \frac{1}{6}\pi$$

```
> epsilon:=-t/365.25*2*Pi;
```

$$\varepsilon := -.3887748118\ \pi$$

```
> theta:=t*(1+1/365.25)*2*Pi;
```

$$\theta := 142.3887748\ \pi$$

```
> SB:=evalf(SunBearing); SB2:=round(SB); SunBearingTrue:=SB2
mod 360 + SB-SB2;
```

$$SB := 173.7499191$$

$$SB2 := 174$$

$$SunBearingTrue := 173.7499191$$

```
>
SunDeclinationFromOverhead:=evalf(SunDeclinationFromOverhead_F
);
```

$$SunDeclinationFromOverhead := 48.29020857$$

```
> SunOffsetFromPanelDegs:=evalf(SunOffsetFromPanelDegs_F);
PowerRelativeToDirectNormal:=evalf(AimFactor);
```

$$SunOffsetFromPanelDegs := 18.69101910$$

$$PowerRelativeToDirectNormal := .9472605210$$

```
> DPE:=evalf(DPE_F); DPN:=evalf(DPN_F);
PB:=evalf(PanelBearing); PB2:=round(PB); PanelBearingTrue:=PB2
mod 360 + PB-PB2;
BE:=SunBearingTrue-PanelBearingTrue; BE2:=round(BE);
BearingError:=(BE2 +180) mod 360 -180 + BE-BE2;
```

$$DPE := .3\ 10^{-10}$$

$$DPN := -.5000000001$$

$$PB := 180.0000000$$

$$PB2 := 180$$

$$PanelBearingTrue := 180.0000000$$

$$BE := -6.2500809$$

$$BE2 := -6$$

$$BearingError := -6.2500809$$

```
> PanelDeclination:=evalf(PanelDeclination_F);
DeclinationError:=SunDeclinationFromOverhead-PanelDeclination;
```

$$PanelDeclination := 29.99999993$$

$$DeclinationError := 18.29020864$$

```
>
```

8 References

1 Accel 2 MJ Superconducting Magnetic Energy Storage, (website), <www.accel.de/pages/2_mj_superconducting_magnetic_energy_storage_smes.html>

2 Air Force Research Laboratory AFRL, (website), <www.afrlhorizons.com/Briefs/Dec01/ML0009.html>

3 Anglesey wind and energy Ltd, (website), <www.anglesey-wind.co.uk/HydrogenSystems/Index1.htm>

4 Baladi et al, 1998, Residential response to voluntary time-of-use electricity rates, Resource and energy economics 20 (1998) 225-244

5 The Biomass Group, Anaerobic digestion, website <http://www.esru.strath.ac.uk/EandE/Web_sites/03-04/biomass/index.html>

6 Boyles D., 1984, Bio-energy technology, thermodynamics and costs, Chichester Horwood

7 DRAM, Demand response and advanced metering coalition, (website), <http://www.dramcoalition.org/>

8 DTI, Energy consumption in the UK, 2002 (update 2003) (website), <www.dti.gov.uk/energy/inform/energy_consumption/index.shtml>

9 DTI, Energy flow chart 2001, <http://www.dti.gov.uk/energy/inform/index.shtml>

10 DTI, Energy statistics: Electricity, 2003, (website), <www.dti.gov.uk/energy/inform/energy_stats/electricity/index.shtml>

11 DTI, Energy trends 2003, (website), <www.dti.gov.uk/energy/inform/energy_trends/index.shtml>

12 Edison Mission Energy, Energy storage and Renewables, (website), <http://www.ee.qub.ac.uk/blowing/activity/UMIST/WS3_Derek_Lumb.pdf>

13 Elecson deep-cycle batteries, (website), <www.unlimited-power.co.uk/deep_cycle_battery_carbon_fibre_elecsol.html>

14 Elexon, (website), <www.elexon.co.uk>

15 Elster, Energy Axis A3 advance meter (website), <www.elsterelectricity.com/>

16 Energy Networks Association (website) <www.energynetworks.org>

17 Filippini, 1994, Swiss residential demand for electricity by time-of-use, Resource and energy economics 17 (1995) 281-290

18 Filippini, 1995, Electricity demand by time of use, Energy economics 17 No 3 (1995) pp197-204

19 IEE, 2000, Embedded Generation, Power and energy series 31

20 IEE Power Engineer, Aug/Sep 2004 p13, “Just in time or just too late?”

21 JRC, Joint Radio Company, (website), <www.jrc.co.uk/products/>

22 Lafferty et al, 2001, Demand responsiveness in electricity markets <www.eere.energy.gov>

23 McMullan R., Environmental science in building, fifth edition 2002, Palgrave

24 MetalsUniverse.com, (website), <www.azom.com/details.asp?ArticleID=1123>

25 National Grid documents & downloads, (2002), (website), <http://www.nationalgrid.com/uk/library/documents/sys_02/downloads/downloads_allfigs.htm>

26 NEDRI, 2003, New England demand response initiative, Dimensions of Demand Response: Capturing Customer Based Resources in New England's Power Systems and Markets, <nedri.raabassociates.org/>

27 NETA New Electricity Trading Arrangements, Balancing mechanism (website) <www.bmreports.com/bwx_reporting.htm>

28 NIA, 2000, World wide power summary 2000, (website), <www.niauk.org/article_31.shtml>

29 Regenerative power and motion, (website), < www.geocities.com/dfradella/basics.htm>

30 Sheen et al, 1994, Response of large industrial customers to electricity pricing by voluntary time-of-use in Taiwan, IEE proceedings in generation, transmission and distribution, vol 142 No 2, 1995

31 Toolbase services, (website), <www.toolbase.org/tertiaryT.asp?DocumentID=2081&CategoryID=966>

32 MET office past data, (website), < www.meto.gov.uk/climate/uk/>

33 Wilkipedia, (website), <en.wikipedia.org/wiki/Superconducting_magnetic_energy_storage>