DEPARTMENT OF ARCHITECTURE

University of Strathclyde Engineering

Variable Energy Pricing in Stand Alone Community Hybrid Energy Systems

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by Callum Rae

A thesis presented in fulfilment of the requirements for the degree of Doctor of Philosophy.

Department of Architecture
James Weir Building
University of Strathclyde
75 Montrose Street
Glasgow G1 1XJ
Scotland, UK

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: ____________________________________

Date: ____________________________________

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Abstract

Satisfying the demand for a more efficient and sustainable energy supply model has presented a new challenge for the energy industry. It has also created an opportunity for alternative and renewable sources of energy generation, which has led to a significant increase in the deployment of renewable technologies in many countries. Recent years have also seen these technologies deployed at a community scale, with remote and isolated communities in particular being regarded as ideal locations. Such systems are capable of providing increasingly viable, stand-alone alternatives to the centralised energy supply model.

This thesis investigates the extent to which the viability of these stand-alone hybrid energy systems could be further improved by implementing domestic demand response, promoted via variable domestic energy pricing. A high resolution, disaggregated model of domestic energy demand at the community level is then developed, supported by the findings of a targeted consumer attitudes survey. This model is combined with a series of demand response algorithms which replicate the response of domestic consumers to energy price variation. Three variable pricing approaches are then applied to the model under a range of conditions, and the impacts examined from both a community-wide and household level perspective.

The thesis demonstrates the relevance and potential of stand-alone hybrid applications and the remote/isolated communities in which they are typically deployed. The results find variable domestic energy pricing based on renewable energy supply to be capable of achieving modest yet significant levels of demand response under a broad range of conditions (83% of the scenarios modelled). Further sensitivity analysis shows the pricing strategies to be resilient to changes in

supply conditions, thereby illustrating the broad ranging potential of such an approach. However, susceptibility to free-rider behaviour and insensitivity to household elasticity levels suggest the need for additional/supplementary forms of financial incentivisation.

List of Abbreviations

SAHES	Stand Alone Hybrid Energy Systems
LZCT	Low and Zero Carbon Technologies
PV	Photovoltaics
NPC	Net Present Cost
SAP	Standard Assessment Procedure
CSH	Code for Sustainable Homes
PHEV	Plug in Hybrid Electric Vehicles
DR	Demand Response
CPED	Consumer Price Elasticity of Demand
CES	Constant Elasticity of Substitution
DSM	Demand Side Management
RES	Renewable Energy Supply
PTR	Peak Time Rebates
ToU	Time of Use
VToU	Variable Time of Use
CPP	Critical Peak Pricing
VCPP	Variable Critical Peak Pricing
RTP	Real Time Pricing
CPED	Consumer Price Elasticity of Demand

Chapter 1: Future Energy Systems

1.1 Future Energy Systems

The threat of climate change combined with the continued depletion of fossil fuel reserves has, in recent decades, created a demand for a more efficient, sustainable energy supply model that lessens mankind's impact on the environment and promotes a less energy-intensive way of life. Satisfying this demand has presented a new challenge for the energy supply industry and requires the updating and renewal of well-established energy systems which have been in place in some cases for the best part of a century. It has also created an opportunity for alternative and renewable sources of energy generation and has led to a significant increase in the deployment of renewable technologies in many countries, in the drive to reduce carbon emissions.

Recent years have seen low carbon and renewable energy systems successfully deployed at large scales, but in order to fulfil their considerable potential and meet ambitious carbon emissions reduction targets, these systems must also be applied at a smaller, localised scale. This represents a shift away from the historically dominant, large scale, centralised energy supply model towards a more distributed model, where energy is generated, stored and consumed locally. Locally embedded and distributed energy projects are now increasingly seen as a viable and preferable alternative to the traditional model, and have been shown to be capable of delivering benefits which range from increased security of supply for stakeholders to local economic benefits (Chicco & Mancarella 2009; del Rio & Burguillo 2008) as well as reduced environmental impact.

The constraints and disadvantages of centralised, fossil fuel based energy supply models are now widely acknowledged, and this is now beginning to incentivise the switch to a more distributed, low carbon alternative. One major contributing factor has been the recent volatility in the price of the fossil fuels, which has been driven primarily by scarcity and uncertainty, caused in particular by geo-political tension in resource-rich regions. This has counteracted the high costs of some low carbon and renewable technologies which are in some cases still technically immature. The production and installation costs of these technologies are expected to continue to drop as expertise and experience increase in conjunction with production efficiency and as improvements in economies of scale are developed (Arent et al. 2011). The ability of distributed energy to provide greater security and quality of supply incentivises its use, as do the financial incentives introduced by governments across the world to encourage the deployment of renewable energy technologies (though there is also significant uncertainty regarding the long term security of these incentives). The result of the above is an environmental, political, economic, technical and social environment in which locally generated and locally owned/ managed energy systems are seen as being increasingly desirable (Chicco & Mancarella 2009).

The areas of society for which the incentive to adopt such systems is greatest is in communities which are worst served by the existing centralised model, namely remote and isolated communities (Rae & Bradley 2013). Here, at the outer limits of the centralised energy model, the cost of energy is often higher than in more urban areas, and the security and reliability of energy supply lower. At the same time, the utilisation of often considerable local renewable energy resources is often severely constrained. As a result of these factors, it is these areas which have established themselves at the forefront of the research and development of Stand-Alone Hybrid Energy Systems (SAHES) (del Rio & Burguillo 2008; Diaz et al. 2010; Shamsuzzoha et al. 2011)

1.2 Demand Response and the Role of the Consumer

One key distinction between the historic/traditional centralised energy model and the decentralised model is the relationship between energy suppliers and energy consumers. Traditionally, the centralised model has taken a reactive approach - observing and predicting changes in demand and adapting supply accordingly, so as to ensure demands are met. However, a key feature of the emerging decentralised/distributed model is the more active role played by the consumer, which has a profound impact on the way in which we view energy and is lessening the traditionally high degree of perceived separation between the typical consumer and energy generation (Verbong et al. 2013; Gangale et al. 2013; Stern 1999).

By introducing the ability for demand to respond to supply, as well as vice-versa, the imbalance in the relationship between supply and demand can be redressed. This concept is referred to as Demand Response (DR), and is capable of bringing a host of benefits to consumers, generators and suppliers of energy (Conchado & Linares 2012; Finn et al. 2012; Albadi & El-Saadany 2008).

There are many ways in which to encourage consumers to engage in DR. These range from more passive approaches such as educating and informing consumers as to the wider benefits of managing their energy consumption, to more active approaches which can involve loads being disconnected in accordance with pre-determined agreements between consumers and suppliers.

One possible approach to encourage consumers to engage in DR is through the introduction of variable energy pricing. This term refers to a pricing tariff or strategy which involves temporal variations in the price of energy. The primary aim of this approach is the promotion of change in the temporal and magnitudinal consumption of energy, based on the fact that consumers are likely to consume more energy when prices are low, and consume less when prices are high. This approach to the promotion of DR has been used for decades, under various guises, and is seen as an area of considerable potential, due to the combination of the following primary factors:

- The increasing need to explore alternative approaches to the generation and consumption of energy.
- The ongoing volatility in the cost of energy, and the desire of consumers to minimise their energy bills.
- The ability of emerging metering and control technology to facilitate more complex forms of energy pricing and consumption control.

Whilst originally deployed at an industrial scale, there is growing consensus that price-based DR can also be utilised at both commercial and domestic scales (Berry 1993; Hammerstrom & Ambrosio 2007; Torriti et al. 2010). This project focusses on the application of variable energy pricing at the domestic level which, in comparison to commercial and industrial applications, presents a unique challenge given the influence of socio-economic and behavioural factors on domestic consumption (Jackson & Surrey 2005; Druckman & Jackson 2008). As such, the domestic sector is seen as having considerable and as yet under-utilised potential.

The potential benefits of price-based DR are of particular relevance in the aforementioned remote and isolated communities. However, the broad range of industries e.g. agriculture, fishing, forestry, tourism etc. and the varying extent of commercial activity found in remote and isolated communities means that the industrial and commercial elements of energy consumption cannot be easily characterised. Whilst these sectors are undoubtedly able to contribute to community-level DR, their inclusion would require a level of specificity (regarding business activity, size etc.) that would limit the transferability of findings. For these reasons, this project focusses exclusively on domestic DR.

1.3 Thesis Objectives

The primary research question addressed by this thesis is as follows:

> *To what extent can variable energy pricing strategies be used to effectively promote domestic demand response in stand-alone hybrid energy systems?*

In order to meaningfully address this question, the following objectives were defined:

1. Establish the relevance of SAHES in the transition towards a more decentralised energy supply model, particularly within the remote and isolated communities in which they are found. This includes the identification of the key challenges and opportunities which exist in this context.
2. Establish the likelihood of the future widespread adoption of flexible energy consumption behaviour in SAHES.
3. Review the existing literature regarding the design and implementation (both theoretical and practical) of variable domestic energy pricing.

4. Generate a high resolution energy consumption model which is typical of a community that is served by a SAHES.
5. Identify one or more variable energy pricing strategies which could be adapted to suit the context of SAHES by using the intermittent energy supply associated with hybrid renewable energy systems as the basis for energy price variation.
6. Develop a model which replicates domestic DR to varying energy prices.
7. Develop a model capable of simulating the implementation of variable pricing strategies in SAHES, and the resulting DR.
8. Identify the key technical, social and economic factors affecting the viability of variable energy pricing in SAHES, based on the outcomes of the modelling process described above.

This thesis sets out to meet each of these objectives, and in doing so, address the primary research question.

These steps also illustrate the over-arching research methodology adopted throughout the project. This involved using both quantitative and qualitative exploration of the subject area, through a combination of extensive and broad-ranging literature review and a consumer survey, to inform a quantitative modelling and simulation process. The analysis of the results of this process then formed the basis for the findings of the project, which are then related back to the subject area. Each of these main areas of the project were guided by their own specific methodologies, which are presented in more detail in the relevant chapters of this thesis.

1.4 Scope and focus of thesis

An intervention such as variable energy pricing has economic, technical and social implications. All three of these aspects must be considered before such an intervention can be deemed sustainable and therefore worthy of further investigation and eventual deployment. Rather than focus on one individual aspect, this thesis aims to establish the high-level economic, technical and social viability of the use of variable energy pricing as a means of promoting domestic DR in SAHES. This aim reflects the highly inter-related nature of all three aspects, and the need for the successful demonstration of the practicability of all three, in order to effectively gauge the potential of the proposed approach. For this reason, a narrower, more focussed approach relating to just one aspect was considered inappropriate. Given the novelty of the approach and the lack of existing knowledge surrounding the use of variable energy pricing in SAHES, a high-level analysis was also deemed appropriate.

1.4.1 Thesis scope

As described above, this thesis will include a high-level analysis of the social, technical and economic impacts which could arise from the introduction of variable domestic energy pricing within the context of SAHES at the community level.

The following subject areas have ***not*** been included within the scope of the project:

- The use of additional renewable energy technologies by individual households.
- The application of variable energy pricing in grid-connected hybrid energy systems.
- Non-electric aspects of domestic energy consumption e.g. non-electric heating and cooking.

- In-depth analysis of the impact of DR and load control on power electronic variables such as frequency regulation, voltage control, network congestion and design etc.
- The viability of implementing the proposed energy pricing strategies in commercial or industrial applications.
- In-depth cost analysis of SAHES project funding and finance mechanisms.
- The potential impact on viability that may be caused by Plug-in Hybrid Electric Vehicles (PHEV's).

The reasons for excluding these areas from the scope of this project are addressed as they arise throughout the thesis.

1.4.2 Limitations of approach

It is important to acknowledge the limitations of the approach outlined above. In particular, it should be noted that whilst the technical, economic and social impacts of variable energy pricing can be meaningfully gauged at a high level, such an approach does not cater for some of the challenges and barriers that may be uncovered by a more detailed approach. However, as stated in the previous section, such a level of detail falls outwith the scope of this thesis.

The approach taken uses information and knowledge from literature and real world examples wherever possible, in order to maximise the accuracy of the results generated. But due to the novel nature of the project (stemming primarily from the context to which variable energy pricing strategies are applied) there are information gaps which have been filled with a series of assumptions. While these assumptions are guided by related literature and informed judgement, it must be acknowledged that they create scope for inaccuracy, particularly when assumptions are made regarding complex socio-economic and behavioural phenomena. Every effort has been made to identify and justify such assumptions as they arise in the thesis, and to minimise any associated uncertainty wherever possible.

1.5 Publications Arising from Thesis

As part of the ongoing development of this thesis, the following journal publications have been produced:

1. C. Rae and F. Bradley. "The Emergence of Low Carbon Energy Autonomy in Isolated Communities." *Journal of Technology Innovations in Renewable Energy* 2.3 (2013): 205-221.
2. C. Rae and F. Bradley. "Energy autonomy in sustainable communities — A review of key issues." *Renewable and Sustainable Energy Reviews* 16.9 (2012): 6497-6506.

In addition, the following conference presentations have been produced:

1. C. Rae. “The Importance of Human Behaviour in the Success of Sustainable Communities”, 22nd International Association of People-Environment Studies Conference, Glasgow, UK, 24-29 June 2012.

The following are poster presentations:

1. C. Rae and F. Bradley. “The viability of variable energy pricing in stand-alone energy systems”, CIRED Workshop, Rome, Italy, 11-12 June 2014.
2. C. Rae and F. Bradley. “Promoting socially viable demand response in stand-alone energy systems using variable energy pricing”, Energy Systems Conference, London, UK, 24-25 June 2014.

1.6 Thesis Summary

The structure of this thesis mirrors the objectives set out in section 1.3, and reflects the gradual narrowing of project focus which occurred over its duration.

Chapter 2 provides a review of the academic literature related to SAHES, and outlines their central role in influencing and informing the shift towards sustainable energy supply and consumption models.

Chapter 3 then examines the literature surrounding domestic energy consumption, and discusses the concept of domestic DR in more detail, both in general, and within the context of SAHES.

Chapter 4 includes the concept of variable energy pricing, including an overview of the different approaches which exist in theory, and the key issues involved in its use. Again, a general overview is provided in addition to a review of more context-specific factors.

Chapter 5 presents the results of a consumer survey, conducted with the aim of gauging consumer attitudes towards domestic DR in the UK, with particular focus on differences in attitudes which exist across different community types and locations. Attitudes towards DR and the role of DR-related technology in the home are also examined.

Having established both the importance of SAHES and the role that can be played by variable energy pricing, **Chapter 6** then moves on to address the issue of how best to simulate consumer response to varying energy prices. This is done through the development of a community scale model of consumption, which represents a generic SAHES and the energy demand and supply associated with it. This model provides the basis for the implementation of selected variable pricing strategies, which are also presented in this chapter. The results of the application of these strategies to the model are then presented in **Chapter 7**, and the results and implications discussed.

Chapter 8 moves on to examine the impact on the results caused by variation in a number of key variables. These sensitivity analyses provide a broader view of the potential of variable energy pricing in SAHES.

Conclusions are then drawn in **Chapter 9**, and the applications and impact of the project are discussed, along with the potential for future work.

1.7 References for Chapter 1

Albadi, M.H. & El-Saadany, E.F., 2008. A summary of demand response in electricity markets. *Electric Power Systems Research*, 78(11), pp.1989–1996. Available at: http://www.sciencedirect.com/science/article/pii/S0378779608001272.

Arent, D.J., Wise, A. & Gelman, R., 2011. The status and prospects of renewable energy for combating global warming. *Energy Economics*, 33(4), pp.584–593. Available at: http://www.sciencedirect.com/science/article/pii/S0140988310001908.

Berry, L., 1993. A review of the market penetration of US residential and commercial demand-side management programmes. *Energy Policy*, 21(1), pp.53–67. Available at: http://www.sciencedirect.com/science/article/pii/030142159390208W.

Chicco, G. & Mancarella, P., 2009. Distributed multi-generation: A comprehensive view. *Renewable and Sustainable Energy Reviews*, 13(3), pp.535–551. Available at: http://www.sciencedirect.com/science/article/pii/S1364032107001578.

Conchado, A. & Linares, P., 2012. The Economic Impact of Demand-Response Programs on Power Systems. A Survey of the State of the Art. In A. Sorokin et al., eds. *Handbook of Networks in Power Systems I SE - 11*. Energy Systems. Springer Berlin Heidelberg, pp. 281–301. Available at: http://dx.doi.org/10.1007/978-3-642-23193-3_11.

Diaz, P. et al., 2010. FAR from the grid: A rural electrification field study. *Renewable Energy*, 35(12), pp.2829–2834. Available at: http://www.sciencedirect.com/science/article/pii/S0960148110002235.

Druckman, A. & Jackson, T., 2008. Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy*, 36(8), pp.3177–3192. Available at: http://www.sciencedirect.com/science/article/pii/S0301421508001559 [Accessed December 12, 2014].

Finn, P., Fitzpatrick, C. & Connolly, D., 2012. Demand side management of electric car charging: Benefits for consumer and grid. *Energy*, 42(1), pp.358–363. Available at: http://www.sciencedirect.com/science/article/pii/S0360544212002435.

Gangale, F., Mengolini, A. & Onyeji, I., 2013. Consumer engagement: An insight from smart grid projects in Europe. *Energy Policy*, 60, pp.621–628.

Hammerstrom, D. & Ambrosio, R., 2007. *Pacific Northwest GridWise^{TM} Testbed Demonstration Projects; Part 1: Olympic Peninsula Project*, Available at: http://sites.energetics.com/MADRI/toolbox/pdfs/pricing/pnnl_2007_pacific_nw_gridwise_olympic_peninsula.pdf [Accessed August 28, 2013].

Jackson, T. & Surrey, G., 2005. Motivating Sustainable Consumption: a review of evidence on consumer behaviour and behavioural change. *A report to the Sustainable Development Research Network*. Available at: https://www.c2p2online.com/documents/MotivatingSC.pdf.

Rae, C. & Bradley, F., 2013. The Emergence of Low Carbon Energy Autonomy in Isolated Communities. *Journal of Technology Innovations in Renewable Energy*, 2(3), pp.205–221. Available at: http://www.lifescienceglobal.com/home/cart?view=product&id=726.

del Rio, P. & Burguillo, M., 2008. An empirical analysis of the impact of renewable energy deployment on local sustainability. *Renewable and Sustainable Energy Reviews*, 13(6-7), pp.1314–1325. Available at: http://www.sciencedirect.com/science/article/pii/S1364032108001044.

Shamsuzzoha, A.H.M., Grant, A. & Clarke, J., 2011. Implementation of renewable energy in Scottish rural area: A social study. *Renewable and Sustainable Energy Reviews*.

Stern, P., 1999. Information, Incentives, and Proenvironmental Consumer Behavior. *Journal of Consumer Policy*, 22(4), pp.461–478. Available at: http://dx.doi.org/10.1023/A:1006211709570.

Torriti, J., Hassan, M.G. & Leach, M., 2010. Demand response experience in Europe: Policies, programmes and implementation. *Energy*, 35(4), pp.1575–1583. Available at: http://www.sciencedirect.com/science/article/pii/S0360544209002060.

Verbong, G.P.J., Beemsterboer, S. & Sengers, F., 2013. Smart grids or smart users? Involving users in developing a low carbon electricity economy. *Energy Policy*, 52, pp.117–125.

Chapter 2: Stand-Alone Hybrid Energy Systems

2.1 The Role of Remote and Isolated Communities in the Changing Energy Model

As part of the response to the triple challenges of growing global energy demand, fossil fuel depletion and increasing GHG emissions, recent decades have seen the gradual emergence of various Low and Zero Carbon Technologies (LZCTs) designed to harness natural energy resources. Significant progress has been made regarding LZCT capability and viability as reliable sources of energy generation and this has led to rapid growth in their deployment around the world, with global installed renewable energy capacity thought to be in the region of 1,900GW, and accounting for around 20% of global energy consumption (REN21 2015).

Whilst the most successful and widespread LZCT deployment has primarily been at a large scale, improvements in manufacturing, economies of scale, miniaturisation and efficiency have meant that smaller scale technologies are now also seen as technically and financially viable (Sorensen 2011; Bull 2001). The growth of medium to micro scale LZCT's has been supported in many countries through government-led financial incentives, such as the UK's "Feed In Tariff" scheme. Such schemes are common, particularly across Europe, and have been largely successful, with some authors arguing that these schemes are the most effective way of promoting renewable energy use (Couture & Gagnon 2010).

The significant increase in renewable energy generation has also been driven by the introduction of European Union (EU) legislation in recent years, which has set targets for the reduction of energy consumption and greenhouse gas (GHG) emissions, including the specific target of reducing GHG emissions to a level of between 80 – 95% of 1990 levels by 2050 (European Commission 2011). The EU has also agreed a series of ambitious targets to be achieved by 2020, relating to energy-efficiency and carbon reduction, demanding a 20% increase in the EU's energy efficiency; a 20% reduction in GHG emissions (relative to 1990 levels) and an increase in the use of renewable energy to 20% of total energy generated (European Commission 2008).

This legislation combined with a growing awareness of global sustainability issues and emissions reductions has incentivised the aforementioned increase in the viability of small to medium scale LZCT's in recent years which has led to the emergence of LZCT-based community-scale energy systems. Many of these projects have emerged in isolated communities, where access to centralised energy infrastructure is limited (Kanase-Patil et al. 2010; Singal et al. 2007; Rae & Bradley 2013). Indeed, more than 50% of European islands are unconnected to any form of central energy supply infrastructure, which can lead to a host of technical and economic challenges. In these instances, SAHES are seen as increasingly preferable alternatives to costly and potentially unreliable energy imports. The particular economic, environmental and social challenges presented in these cases has led to good examples of technical innovation and therefore despite the fact that isolated communities represent a small (and decreasing) proportion of the industrialised world's total population (The World Bank 2011), they have inadvertently emerged at the forefront of research and development into SAHES.

Despite increasing global urbanisation, the role of isolated communities is considered to be highly significant when it comes to sustainable energy development. This is reflected in the abundance of research projects adopting isolated communities as a vehicle through which to study the application and implementation of SAHES, including but not limited to (Duic et al. 2008; Michalena & Angeon 2009; Gazey et al. 2006; Ntziachristos et al. 2005; Prodromidis & Coutelieris 2010; Young et al. 2007).

Isolated communities can be defined as settlements which are geographically removed from population centres to the extent that they fall outwith the immediate sphere of influence of their nearest population centre(s). The following are listed by (Underwood et al. 2007) and (Hanley & Nevin 1999) as being characteristics which can be considered typical of isolated or remote communities:

- Low population density;
- Limited conventional energy resources;
- Lack of infrastructure;
- Low levels of economic activity;
- Physical access constraints;
- Long distances to external markets.

The prominent role of isolated communities within the context of changing energy supply models is largely attributable to these characteristics, as they ensure that isolated communities stand to gain more from increased levels of energy autonomy than other areas of society. This makes isolated communities the ideal test-bed for SAHES.

From an academic perspective, there may be other reasons for the emergence of numerous remote/island-based studies. For example, the existence of clear and geographically defined boundaries that exist for island and off-grid energy systems means that other relevant system boundaries (be they social, economic or technical) can be clearly defined and measured, making for more easily obtainable and quantifiable results. Also, as identified in Hain et al. (Hain et al. 2005), remote (and in particular rural) community-level projects are ideal for the application of the principles of sustainable energy autonomy (also referred to as energy autarky (Muller et al. 2011)). This stems from the fact that they can be seen as having the most to gain, thanks in part to their need to diversify land use. This makes them ideal for onshore wind energy and the cultivation of biofuels. Hain et al. also identify the receptive and often more knowledgeable approach towards renewable energy shown by rural communities as being another contributing factor, although there are of course exceptions to this generalisation. As a result of both necessity and their clearly defined, often small-scale nature, these communities have acted as the testing ground for the methods, practices and technologies involved in the development of hybrid and alternative energy systems, and in particular SAHES (Michalena & Angeon 2009; Young et al. 2007; Kaldellis et al. 2009; Giatrakos et al. 2009; Chen et al. 2007; Indradip 2006).

2.1.1 Industrialisation and the emergence of the current energy supply model

In the years preceding the widespread use of fossil fuels, the energy available for human consumption was limited to the following sources:

- plant photosynthesis - energy which is captured by plant life and used to fuel either fire or mechanical work done by humans or by animals;
- The elements - via early wind, solar, run-of-river and tidal energy installations.

These sources were the basis for what Wrigley defines as ‘organic economies’, and served to place considerable constraints on energy consumption (Wrigley 2013). Trading in fuels during this period was likely to have been confined to a regional scale, given the low energy density of fuels such as fire wood, and whilst the level of energy provision enjoyed by historic communities was not comparable to that of today, it can be seen as being truly distributed and more sustainable at a local level.

During the industrial revolution of the 19th Century, the ability to harness energy from fossil fuels on an industrial scale provided access to highly concentrated quantities of photosynthesised energy, thereby breaking the cycle of reliance on short-term crop yields. With a (seemingly) abundant supply of high energy fuel, combined with the rapid scientific and engineering advancement of varied technologies for utilising it, industrial productivity soared. This period marked the beginning of mankind’s dependence on fossil fuels, and also the beginning of a rapid centralisation of populations within industrialising countries. Inevitably, access to energy sources was greater in population centres than in isolated rural areas and therefore rural communities were essentially ‘left behind’ as the industrial age gathered momentum across Europe and the world. The establishment and later expansion of national centralised energy supply and generation infrastructure in the 20th century partly addressed this disparity, but the high cost of extending grid infrastructure to small and remote communities ensured that many communities remained without access to grid electricity.

Since the establishment of these large, centralised energy models, energy supply in isolated communities has therefore been characterised by a reliance on energy imports from population centres. These imports typically consist of fossil fuels, such as diesel for the running of generators for electricity, or fuel oil for use in heating system boilers.

2.1.2 Issues resulting from the current energy supply model

In an attempt to improve security of supply and move away from a reliance on fuel imports across national boundaries, efforts have been made in recent years to integrate increasing amounts of renewable energy generation into national energy networks. Although this helps to reduce a country's vulnerability to the geo-political instability which surrounds fossil-fuel rich regions (Krajačić et al. 2011) and attempts to address the inherent scarcity of fossil fuels (being a finite resource), this change towards LZCT-based generation can give rise to other security of supply concerns at a regional level rather than an international level (Ofgem 2012). For example, the disruption of transportation supply routes due to adverse weather conditions, or the dependence on delivery methods which are unreliable, can cut communities off from their source of supply. Ironically, despite the best quality and quantity of renewable energy resources often being found in remote/isolated areas, the centralised nature of existing infrastructure makes it ill equipped to exploit these often vast resources.

Another major impact of the centralised energy supply model is its tendency to contribute towards the centralisation of population, as young members of isolated communities are attracted by improved employment prospects and a perceived higher quality of life in urban population centres. This results in a 'talent drain' that sees young, skilled workers migrate to urban population centres with a resultant 'greying' effect on the remaining population. This trend is exacerbated by the decline in traditional rural industries such as agriculture, mining and fishing (DEFRA 2004).

2.2 Advantages and Opportunities

As discussed above, isolated communities are particularly badly served by the prevailing energy supply model. However, in recent years the emergence of SAHES has provided increasingly viable alternatives to the existing centralised model. This section discusses the range of factors which make many isolated communities ideal for the deployment of SAHES, and identifies some of the key drivers.

2.2.1 Renewable energy resources

Remote areas tend to have greater access to renewable energy resources than others due to favourable climatic conditions and a greater exposure to the elements, due to the lack of interference by human development and the built environment. In addition, low population density in isolated regions means that they have a reduced likelihood of anthropogenic resource depletion e.g. the shading/sheltering effects of buildings which can reduce solar and wind energy yields. This presents one of the principle limitations of the current centralised energy supply model - that its infrastructure is often poorly equipped to utilise these outlying energy resources at the limits of the network. The benefit of improving the infrastructure in order to enable it to utilise these resources is often outweighed by the cost of doing so, meaning that renewable resources remain untapped.

2.2.2 Security of supply

The security of energy supply is an important issue in many isolated communities. This term relates primarily to the reliability of the energy supply network, but is also linked to the diversification of the supply mix in order to spread the risk of disruption in the event that one source of supply becomes unavailable e.g. a sudden and steep increase in oil prices.

There is some debate as to whether or not the emergence of a decentralised energy model will help or hinder security of supply. By any measure, it can certainly be seen to increase diversification. The International Energy Administration (IEA) is amongst those who feel that increased levels of distributed generation will help to mitigate the risk and cost of supply disruptions (Fraser & IEA 2002).

Despite the inherent intermittency of renewable energy resources, they have been shown to be capable of providing an adequate degree of security of supply (Padrón et al. 2011) that is equal to (or even surpasses) that of the current model, provided that adequate storage and system management are used (Arteconi et al. 2012). Del Rio and Burguillo suggest that the ability of LZCT’s to contribute towards the security of energy supply is often overlooked in favour of other socio-economic benefits (del Rio & Burguillo 2008b).

Reliability is a particularly pertinent issue in remote and isolated areas (Ashok 2007; IEA 2010). Even those which do benefit from a connection to national grid infrastructure are often subject to a poorer quality of supply than those in more urban areas due to weaknesses (and resulting unreliability) in infrastructure (Duic et al. 2008; Shamsuzzoha et al. 2011). This has resulted in a secondary research hypothesis being identified - that the level of knowledge, understanding and appreciation for energy supply is likely to be higher in remote and isolated communities. This is discussed in more detail in later chapters.

2.2.3 The cost of energy

Whilst the cost of energy from LZCT’s can be high in comparison to that from grid supplied or off-grid fossil fuel based supply, recent years have shown a marked decrease in the cost of renewable energy (Arent et al. 2011; IPCC 2011). This translates into lower purchase costs and therefore a lower energy cost for the consumer. This gradually increasing financial viability is likely to be compounded by ever rising fossil fuel costs (IEA 2010) which, when coupled with the geo-political security of supply concerns highlighted above, serve to further incentivise LCEA.

There are a number of financial incentives and support systems which have been introduced by various governments aiming to encourage the deployment of renewable energy. These range from grants for the purchase of renewables (BRE n.d.) to ‘green’ investment initiatives designed to encourage private-sector investment in renewable energy (UK Green Investment Bank n.d.). A particularly successful tool in the drive to encourage deployment is feed-in tariffs (FITs), which have been used in several countries (Couture & Gagnon 2010) and were introduced in the UK in 2010. FITs guarantee owners of small and micro-scale renewables a fixed price for the energy they produce. However, as is argued by Haas et al., the promotion of renewable energy technologies through financial incentives alone is not enough to foster widespread deployment and behavioural change (Haas et al. 2004). To achieve these aims instead requires systemic change that includes the provision of training and education and also provides innovative and progressive regulatory initiatives (Willis 2006; Haas et al. 2004).

For the deployment of renewable technologies to be deemed preferable to conventional systems, they must be shown to have a competitive lifetime cost. Walker cites difficulties to market entry and network connection barriers as additional financial disadvantages facing community energy projects, but acknowledges that steps have been taken recently by policy makers to address these difficulties, and goes on to predict an increase in community owned renewable energy projects over the coming years (Walker 2008).

2.2.4 Socio-economic impact

Existing energy supply models in isolated communities can contribute towards some negative socio-economic consequences, such as fuel poverty and limits to the viability of commercial activity. The introduction of SAHES in these instances could therefore play an important role in reversing these trends and have a positive impact on communities. This view is widely supported by the literature (Roseland 2000; Michalena & Angeon 2009; Kaplan 2000; del Rio & Burguillo 2008a).

Arguably the most significant long-term socio-economic benefit of the introduction of a more secure and reliable energy supply is its potential to reverse the trend of ‘greying’ population. This can be achieved by making remote and isolated communities a more attractive prospect both for local young people (perhaps returning from education or looking for employment) and for prospective new residents and visitors. It is thought that this could be achieved both through the creation of additional jobs and through the improved quality of life and services that can result from improved energy supply. All of these help to ensure that profit from the development is retained locally. In addition, supplementary/enabling services that are commonly coupled with the deployment of SAHES - such as the introduction of high-speed internet services - could also help to make such communities more viable for online businesses. An increased sense of community and a more positive perception of LZCT’s have also been found to occur, thereby adding social autonomy to the concept of energy autonomy (Bolinger 2001).

In addition to the diversification of local industry, land use can also be diversified by the introduction of SAHES, thus adding a new dimension to the local economy and creating jobs. The potential for development and growth of sustainable tourism also provides further diversification (del Rio & Burguillo 2008a).

As pointed out by both Del Rio and Burguillo (del Rio & Burguillo 2008a; del Rio & Burguillo 2008b) and Kaundinya (Kaundinya et al. 2009), the potential benefits such as those listed above, whilst perhaps being broadly applicable, are highly case-specific and must be examined in sufficient detail before being associated with any individual community.

2.2.5 Community ownership and stakeholder engagement

The need for those who contribute to and accommodate community energy projects to reap the financial and social benefits they can bring appears to be a widely held stance which is almost universally supported in the literature (Roseland 2000; Kaplan 2000; Michalena & Angeon 2009).

A distinguishing feature of SAHES is the potential for community ownership, which grants the community the opportunity to exert greater control over the design and operation of the local energy system than can be achieved under 'conventional' ownership models. Crucially, it also gives the community greater access to the financial benefits that can result.

Community ownership has been used to successfully incentivise the use of medium to large scale wind energy installations in many European countries. Denmark is a notable example, with community partnerships owning an estimated 80% of Denmark's wind capacity. In addition to bringing significant financial benefits to the participants, this has helped develop the Danish wind energy industry into a world leader. In the UK, the number of renewable energy installations owned by community groups is increasing. In Scotland alone, the capacity of community and locally owned renewable generation capacity increased from 285MW (of which community groups make up 43MW - an increase of 65% on the previous year) to 361MW between June 2013 and June 2014 (Scottish Government 2014). The installations owned solely by community groups are shown in Figure 2-1, which illustrates the prominence of such schemes in rural, remote and isolated communities.

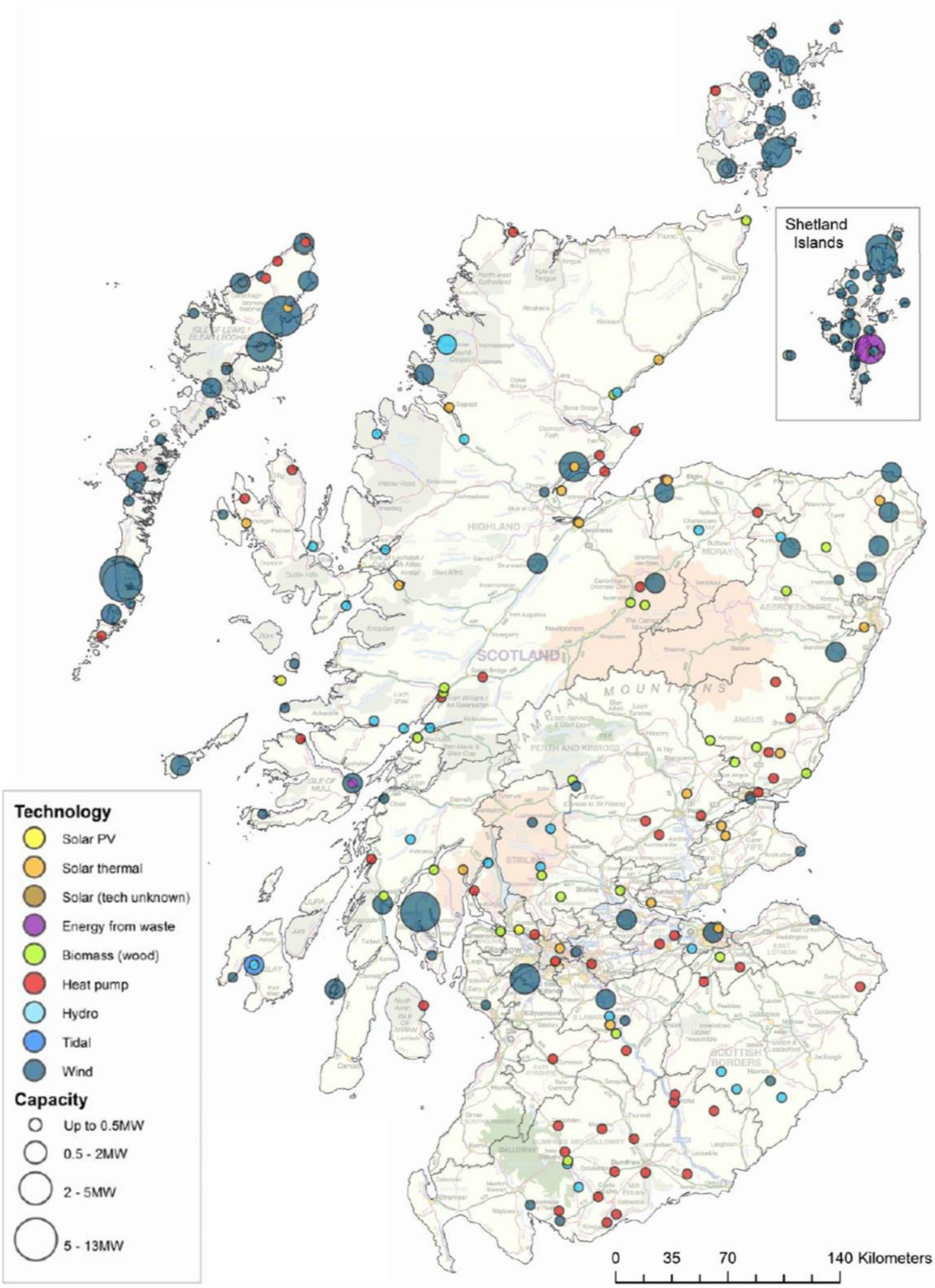


Figure 2-1 - Map showing the size, type and location of renewable energy installations owned by community groups in Scotland (adapted from (Energy Saving Trust 2015)).

The Scottish government have set a target of 500MW of community and locally owned renewable generation capacity by 2020 (Scottish Government n.d.).

The reasons behind the current increase are the host of local economic and social benefits which result from community/shared ownership of LZCT's and SAHES. Community ownership also appears to incentivise technological change, whilst creating a more positive view of the concept of autonomy, and the use of LZCT's. This argument is supported by Warren and McFadyen, who found that communities were less resistive to LZCT development (in the form of wind turbines in this case) if they knew that their community was directly benefitting from their deployment (Warren & McFadyen 2010).

When it comes to engaging stakeholders, the UK serves as a particularly effective demonstration of its importance, given the resistance to large scale renewable energy (particularly wind energy) that has arisen in recent years (Jones & Richard Eiser 2010; Cass & Walker 2009). In fact, a direct correlation between community involvement and reduced resistance to wind energy was found by Warren and McFadyen, who found that whilst community involvement – in the form of ownership – does not transform negative attitudes into positive ones, it does appear to amplify positive attitudes and suppress negative ones. The benefits of increased community engagement and participation within a UK context are also discussed by Walker and Devine-Wright (Walker et al. 2007; Walker & Devine-Wright 2008; Devine-Wright 2005) and also by Rogers et al., who used questionnaires and surveys in order to gauge the opinions and perceptions of various stakeholders (Rogers et al. 2008). Their findings broadly support the idea that stakeholder engagement fosters more favourable local views of sustainability and renewable energy.

Public receptiveness to renewable energy has also been found to alter with scale. Research by Shamsuzzoha et al. found public willingness for smaller local development to be approximately twice as high as willingness to accept large scale development (Shamsuzzoha et al. 2011). This appears to compound the need for stakeholder involvement and the sharing of the benefits between stakeholders. It also hints at another perceived advantage of adopting SAHES - the likelihood of greater than average local receptiveness and the positive engagement of stakeholders.

Interestingly, community ownership also offers consumers an alternative to dealing with large, established energy suppliers. Recent consumer research conducted in the UK suggests that such companies are amongst the least trusted of all major industries, and have the lowest level of customer satisfaction (Strong & Which? 2014).

2.3 Disadvantages and Challenges

Despite being advantageous in some regards, there are also a number of disadvantages and challenges associated with SAHES. These act as barriers to their development and deployment.

2.3.1 LZCT costs

The role of economics and project finance, as in any area of modern society, has a significant (arguably even decisive) impact when it comes to sustainable development and in particular renewable energy. Each renewable energy technology has performance and economic characteristics which make them suitable for some applications and unsuitable for others. The high level of variation in cost and performance capability of these technologies can be seen as being strongly linked to the rate and extent of their deployment.

Despite increasingly efficient manufacturing techniques and improved performance, LZCT often have a higher cost per unit of energy delivered than conventional grid-supplied energy (Hallam & Contreras 2015). The funding of LZCT-based systems also differs from that of conventional diesel-based systems in that the costs are largely ‘front loaded’ i.e. the initial capital cost of the system components themselves represents the majority of the investment required. This disparity stems from the fact that the purchase of fuel is not required for such systems, but represents a significant proportion of the lifetime cost of fuel-based energy systems. This is illustrated by the figures below, which show the cash flow associated with two different energy supply scenarios for the isolated village of Sicud, on the island of Palawan in the western Philippines. These scenarios were developed using a model provided by the developers of HOMER, a software tool developed by the (American) National Renewable Energy Laboratory for the design, optimisation and analysis of hybrid energy systems (NREL n.d.). Figure 2-2 shows the cash flow associated with a system using diesel generation only. Diesel generation is thought to be the most widespread technology in stand-alone power applications, as it is a well-established (and therefore trusted) technology with which many people have a degree of familiarity (Diaz et al. 2010). Figure 2-3 shows the cash flow associated with a SAHES of similar Net Present Cost (NPC) comprising of photovoltaics (PV), wind, and battery storage as well as diesel generation.

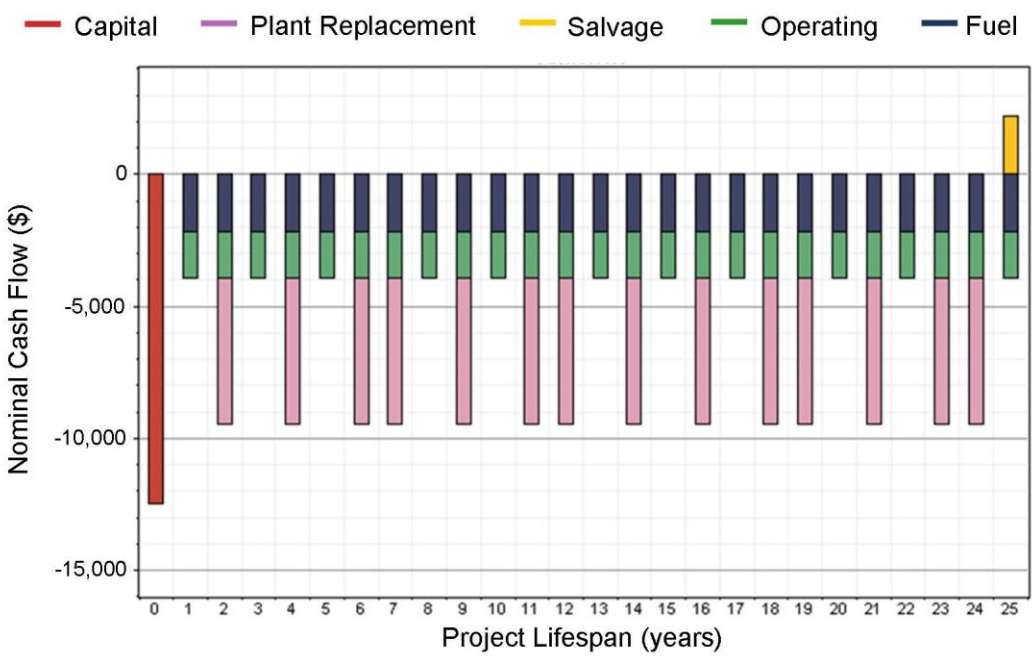


Figure 2-2 - Typical cash flow of diesel only energy system.

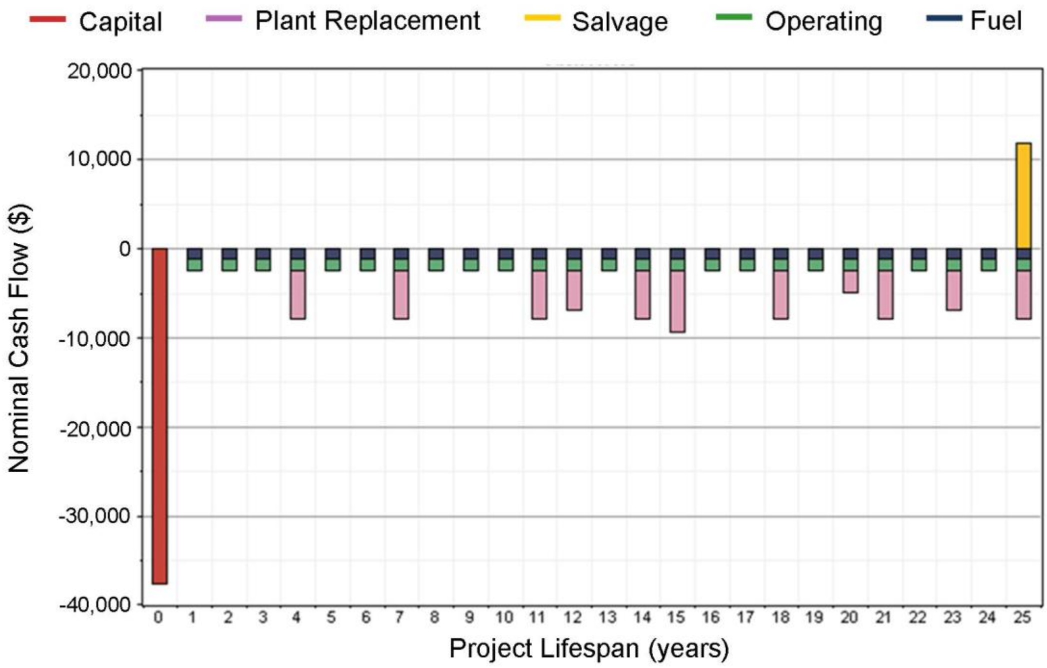


Figure 2-3 - Typical cash flow of diesel/LZCT hybrid energy system.

Although both solutions have similar NPC, the capital cost associated with the hybrid system represents a far higher percentage of the total project cost (45.9%) than in the diesel only system (14.3%), whilst fuel costs represent just 15.5% compared to 27% in the diesel only system. This comparatively high initial cost can act as a barrier to the deployment of on-site renewables, but the financial competitiveness of many LZCT's has improved in recent years, due largely to decreasing production costs, higher efficiencies, and the volatility and long term rising cost of fossil fuel use (Arent et al. 2011).

The above disparity can lead to LZCT-based projects being seen to be overly "capital intensive" compared to more conventional alternatives (IEA 2010). This is compounded by the intermittency of renewable generation and relative immaturity of some LZCT's, which render financial forecasting a more challenging exercise. The current disparity between the level of subsidies enjoyed by the fossil fuel industry and the renewable energy industry is another distinct economic disadvantage. In 2009, global fossil fuel consumption subsidies were approximately $312 billion whilst renewable energy only received $57 billion (IEA 2010). This in turn had a direct effect on energy costs from these sources, and illustrates the extent of the governmental support currently (and also historically) received by the fossil fuel industry. The cost of developing the innovative and (therefore expensive) methods of extraction required to utilise new fossil fuel reserves can also potentially be passed on to consumers. These additional costs should therefore be factored into any cost comparison of continued fossil fuel reliance and LZCT-based alternatives.

2.3.2 The intermittency of renewables

The inherent intermittency of many renewable energy sources presents a number of challenges for energy systems which rely on them. As discussed by Rae and Bradley (Rae & Bradley 2012), the basis for any energy system is the process of matching demand with supply. In systems which rely heavily on intermittent sources of energy e.g. solar, wind or tidal energy, some form of energy storage is usually required in order to ensure that any excess energy which is produced can be stored for use during periods when demand exceeds supply. This is particularly relevant in smaller off-grid energy systems, where variation in patterns of demand are greater than in other areas, and their impact on the balance of the system is therefore also greater (Kaldellis & Zafirakis 2007).

2.3.3 Energy storage

Energy storage involves the capture and storage of energy when supply exceeds demand (surplus), for use in periods when demand exceeds supply (deficit). As discussed above, storage is of particular relevance when it comes to renewable energy, due to its ability to act as a buffer for energy generated by intermittent sources, thereby increasing the penetration and utilisation of renewable energy resources.

In cases where connection to a large energy distribution system is possible i.e., the National Grid or equivalent, this system can serve as a means of energy storage.

However, in cases where such a connection is not possible (as in the case of islands and remote communities) on-site forms of energy storage are required to deal with the differences between demand and supply. Energy storage is therefore regarded as a key research area in the field of SAHES research, with many of the currently available storage solutions being widely acknowledged as underdeveloped, inefficient and expensive.

The choice of energy storage technology in SAHES (as in any other) is largely defined by a set of operational parameters and constraints which serve to make some storage technologies more suited to any particular given application than others (Kaldellis et al. 2009). Typical storage systems include:

- Batteries (including lead-acid, Na–S, Li–ion and flow batteries);
- Fuel cells;
- Pumped hydro storage;
- Flywheels;
- Compressed Air Energy Storage (CAES);
- Super capacitors.

Each of these storage methods is currently at a different level of technical maturity, which means that the more established technologies such as batteries and pumped hydro storage tend to be more widely used than those methods which have been developed more recently, such as fuel cells and super capacitors (Hadjipaschalis et al. 2009; Chen et al. 2009). The various energy storage technologies listed above vary considerably when it comes to installation and maintenance costs, operational lifetime, logistical and spatial requirements. They also vary in scale, with some technologies being better suited to some applications than others. For example, pumped hydro storage would be seen as a far more appropriate storage solution than batteries should the required capacity be several megawatts (MW), with the opposite being true if the capacity was several kilowatts (kW). This is clearly illustrated by Kaldellis et al. where a range of energy storage technologies are subjected to techno-economic performance comparison at a number of scales (Kaldellis et al. 2009).

The development of storage technologies has been the subject of much research in recent years (Kaldellis et al. 2009; Giatrakos et al. 2009; Hadjipaschalis et al. 2009; Young et al. 2007; Ren et al. 2012; Chen et al. 2009; Nair & Garimella 2010; Zoulias & Lymberopoulos 2007; Nkwetta & Haghighat 2014; Xu et al. 2014; Raccichini et al. 2015). This is testament to the prominent role currently played by storage in distributed energy projects in general, and to its potential as a facilitator of cost-effective energy autonomy.

Despite the vital role played by energy storage in many autonomous energy supply systems (particularly off-grid systems) it is often seen as being prohibitively expensive and inefficient (Young et al. 2007; Ren et al. 2012). This is due in part to the unfavourable comparison that arises between a small scale energy storage system, and the ability of grid connected systems to use the grid as a means of energy storage. For example; financial incentives may provide income for energy exported to the national grid, which itself is managed and maintained by external parties, whilst on-site, small scale energy storage represents a significant proportion of overall project cost. However, as is also acknowledged by Young et al., there are certain scenarios and circumstances where typically prohibitively expensive storage technologies are preferential to grid connection i.e., in island or remote regions (Young et al. 2007).

One way of addressing the challenges presented by energy storage is to reduce the extent to which they are required. This can be achieved through improving the match between energy demand and renewable energy supply, which in turn limits the magnitude and duration of periods of renewable energy deficit/surplus, thereby reducing the need for energy storage. The matching of demand and renewable supply is consequently a central theme of this thesis, and will be examined in more detail in later Chapters.

2.3.4 Resistance to renewables

The deployment of LZCT's can be subject to opposition from various sources, which stem from objections to one or more of the following:

- The potential threat posed to local ecosystems, wildlife, plant life etc. through loss of habitat, noise disruption or physical threats from moving parts;
- Perceived negative visual or aural impacts;
- The potential for threats to local air quality (in the case of combustion-based technologies such as biomass);
- Objections relating to the role of LZCT's in the energy supply mix.

These risks all pose obvious and significant barriers to the adoption of SAHES.

2.3.5 Policy and bureaucratic barriers

Another key challenge comes in the form of the existing policy environment. The existing policy and bureaucratic environment has developed over many years, around (and in support of) the traditional centralised energy supply model. The relatively recent and increasingly rapid emergence of LZCT's and their rate of deployment means that in many ways the regulatory and policy environment has struggled to keep up. As a result, numerous authors recognise the need for significant changes to current energy planning and market regulation, in order to encourage the rollout of distributed energy projects and allow renewable energy to fulfil its considerable potential (Roseland 2000; Abu-Sharkh et al. 2006; Willis 2006).

Examples of successful use of policy to encourage renewable energy projects can be found across Europe, in countries such as Denmark, Sweden and Germany. These countries led the way in terms of renewable energy (particularly in wind energy and the concept of community ownership) in the lead up to the turn of the century, thereby establishing themselves as world leaders by providing a supportive policy environment that allowed (and continues to allow) the industry to flourish.

As noted by Hain et al., existing UK government support networks (both financial and planning) have tended to favour large schemes (Hain et al. 2005). This trend is also present in the software tools used to design and plan SAHES (Mendes et al. 2011). Similarly, Walker et al. examine UK renewable energy policy, and note the absence of a “strategic view…(of) what scales or types of projects should be supported” (Walker et al. 2007). Instead, the authors describe the evolution of policy simply as a response to what is proposed at a community level. Perhaps more significantly, it could be argued that policy fails to address the issue of scale, with smaller, community-based projects such as many SAHES being at a disadvantage. However, as discussed above, recent years have seen an improvement in the levels of support available to smaller projects, with a particular focus placed on community projects.

These findings suggest a correlation between the size of community energy projects being proposed/constructed and the size of the organisations behind them. Investment and support is given largely to those proactive organisations which actively seek it, which in the UK tends to be community groups, typically in the form of village/community groups and trusts. A good example of this is the village of Fintry in Scotland who, through the Fintry Development Trust, have sought to put sustainability at the centre of the village’s image and the mind-set of the residents. This has most notably been achieved through the successful negotiation for an additional turbine to be included in a nearby commercial wind farm development, which is owned by the trust. The income this turbine provides has been channelled back into community initiatives such as the provision of building insulation, the installation of micro-renewables and the planting of a village orchard (Fintry Development Trust n.d.). The success of what has been achieved at Fintry has seen the village gain notoriety, and effectively demonstrates the need for (and value of) stakeholder engagement (Warren & McFadyen 2010). This is one of many collaborative projects between energy developers and community groups which have emerged in recent years (Mcewen et al. 2012).

Some authors have called for policy to become more proactive and less reactive, thus shifting the onus towards engaging a broader cross-section of society rather than depending on the proactive minority (such as the example provided above) (Haas et al. 2004; Jackson & Surrey 2005). The literature reviewed also appears to widely favour a bottom-up approach to policy as opposed to a top-down approach, with Kellett demonstrating the effectiveness of community-led initiatives over top-down policy mechanisms, which are described as being insufficient to bring about the changes to policy that are required (Kellett 2007). This view is shared by Rogers (Rogers et al. 2008).

The view that increased levels of government financial support are required in order to allow community-scale energy projects such as SAHES to fulfil their considerable potential is commonly held throughout much of the literature reviewed, and in particular (Roseland 2000; Bolinger 2001; Willis 2006; Walker 2008). Bolinger goes on to argue that UK policies such as the Non-Fossil Fuel Obligation (NFFO) have favoured larger projects led by wealthier and more established organisations instead of following this European model of community led co-operatives (Bolinger 2001). UK policy has since undergone significant changes to better accommodate renewable energy through, for example, the introduction of the Feed In Tariff. It should however be noted that the level of support provided by such fiscal measures are subject to change over time, which itself creates problematic uncertainty. There is therefore still a need for inclusive policy which promotes development at a range of scales and funding/ownership models.

2.4 Conclusions

This chapter has examined the concept of switching from the centralised energy supply model which is prevalent in the industrialised world towards a more autonomous model based on the use of LZCT's. Within this area, SAHES (and the remote and isolated communities in which they are most common) have been identified as being of particular relevance.

The current centralised model can be seen to place remote and isolated communities at a relative disadvantage in comparison with other areas of society. As such, remote and isolated communities have been shown to be the worst served by the existing centralised model, thanks primarily to issues relating to the security of existing infrastructure connections and the cost of the alternatives. This problem is further exacerbated by the fact that many remote and isolated communities are unable to capitalise on often significant local renewable energy resources. When considered in combination, these factors explain the emergence of SAHES in such communities, and their role at the forefront of innovation and deployment when it comes to the adoption of LZCT's. Remote and isolated communities, and SAHES in particular, are therefore seen as an ideal and highly relevant context for further research, which can better inform the transition towards a more decentralised energy model which will potentially be made by other sections of society.

SAHES have been found to be capable of providing energy which is competitive with the existing centralised model both in terms of security and affordability. However, this alone has not proved enough to guarantee their widespread deployment, and a number of significant technical and socio-economic barriers have been identified. The technical challenges associated with the incorporation of on-site energy storage and the intermittency of various renewable technologies adds both complexity and cost. In addition to high capital costs, project finance has also been found to be a major barrier to the further deployment of SAHES.

The need for a receptive social and political environment for SAHES, and in particular community owned projects, has been slow to develop but is now becoming much more clearly understood. The highly case specific nature of these projects makes the task of providing support which is general enough to be broadly applicable, yet specific enough to be tailored to each specific instance, a challenging one. Garnering support at both local and regional scales is also crucial, as lack of perceived community/local benefit and resistance to locally sited renewable energy installations can act as a significant barrier to development.

These challenges and opportunities shape the market and general demand for SAHES, and provide the energy supply context for this research. The next chapter reviews the evolution of research and understanding of domestic energy demand in more detail, and examines the contribution it can make towards DR.

2.5 References for Chapter 2

Abu-Sharkh, S. et al., 2006. Can microgrids make a major contribution to UK energy supply? *Renewable and Sustainable Energy Reviews*, 10(2), pp.78–127. Available at: http://www.sciencedirect.com/science/article/pii/S1364032104001194.

Arent, D.J., Wise, A. & Gelman, R., 2011. The status and prospects of renewable energy for combating global warming. *Energy Economics*, 33(4), pp.584–593. Available at: http://www.sciencedirect.com/science/article/pii/S0140988310001908.

Arteconi, A., Hewitt, N.J. & Polonara, F., 2012. State of the art of thermal storage for demand-side management. *Applied Energy*, 93(0), pp.371–389. Available at: http://www.sciencedirect.com/science/article/pii/S0306261911008415.

Ashok, S., 2007. Optimised model for community-based hybrid energy system. *Renewable Energy*, 32(7), pp.1155–1164. Available at: http://www.sciencedirect.com/science/article/pii/S0960148106000978.

Bolinger, M., 2001. Community wind power ownership schemes in Europe and their relevance to the United States.

BRE, Grant schemes for low carbon and renewable energy systems installation. Available at: http://www.bre.co.uk/page.jsp?id=1332.

Bull, S.R., 2001. Renewable energy today and tomorrow. *Proceedings of the IEEE*, 89(8), pp.1216–1226.

Cass, N. & Walker, G., 2009. Emotion and rationality: The characterisation and evaluation of opposition to renewable energy projects. *Emotion, Space and Society*, 2(1), pp.62–69. Available at: http://www.sciencedirect.com/science/article/pii/S175545860900036X.

Chen, F. et al., 2007. Renewislands-Renewable energy solutions for islands. *Renewable and Sustainable Energy Reviews*, 11(8), pp.1888–1902. Available at: http://www.sciencedirect.com/science/article/pii/S1364032106000232.

Chen, H. et al., 2009. Progress in electrical energy storage system: A critical review. *Progress in Natural Science*, 19(3), pp.291–312. Available at: http://www.sciencedirect.com/science/article/pii/S100200710800381X.

Couture, T. & Gagnon, Y., 2010. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. *Energy Policy*, 38(2), pp.955–965. Available at: http://www.sciencedirect.com/science/article/pii/S0301421509007940.

DEFRA, 2004. Department for Environment, Food and Rural Affairs: Rural Strategy. , 2012(17th December). Available at: http://archive.defra.gov.uk/rural/documents/policy/strategy/rural_strategy_2004.pdf.

Devine-Wright, P., 2005. Local aspects of UK renewable energy development: exploring public beliefs and policy implications. *Local Environment*, 10(1), pp.57–69.

Diaz, P. et al., 2010. FAR from the grid: A rural electrification field study. *Renewable Energy*, 35(12), pp.2829–2834. Available at: http://www.sciencedirect.com/science/article/pii/S0960148110002235.

Duic, N., Krajacic, G. & da Graca Carvalho, M., 2008. RenewIslands methodology for sustainable energy and resource planning for islands. *Renewable and Sustainable Energy Reviews*, 12(4), pp.1032–1062. Available at: http://www.sciencedirect.com/science/article/pii/S1364032106001560.

Energy Saving Trust, 2015. *Community and locally owned renewable energy in Scotland at 2014*, Available at: http://www.energysavingtrust.org.uk/sites/default/files/reports/FINAL Community and locally owned June 2014_v3.pdf.

European Commission, 2008. 20 20 by 2020 Europe's Climate Change Opportunity. *COM (2008)*, 30.

European Commission, 2011. A Roadmap for moving to a competitive low carbon economy in 2050. *COM (2011)*, 112(4). Available at: http://ec.europa.eu/clima/policies/roadmap/index_en.htm.

Fintry Development Trust, fintrydt.org.uk. Available at: http://www.fintrydt.org.uk/index.php?page=history.

Fraser, P. & IEA, 2002. Distributed generation in liberalised electricity markets. In *International symposium on distributed generation: power system and market aspects*. p. 1G–12.

Gazey, R., Salman, S.K. & Aklil-D'Halluin, D.D., 2006. A field application experience of integrating hydrogen technology with wind power in a remote island location. *Journal of Power Sources*, 157(2), pp.841–847. Available at: http://www.sciencedirect.com/science/article/pii/S0378775305016526.

Giatrakos, G.P. et al., 2009. Sustainable energy planning based on a stand-alone hybrid renewableenergy/hydrogen power system: Application in Karpathos island, Greece. *Renewable Energy*, 34(12), pp.2562–2570. Available at: http://www.sciencedirect.com/science/article/pii/S0960148109002614.

Haas, R. et al., 2004. How to promote renewable energy systems successfully and effectively. *Energy Policy*, 32(6), pp.833–839. Available at: http://www.sciencedirect.com/science/article/pii/S0301421502003373.

Hadjipaschalis, I., Poullikkas, A. & Efthimiou, V., 2009. Overview of current and future energy storage technologies for electric power applications. *Renewable and Sustainable Energy Reviews*, 13(6-7), pp.1513–1522. Available at: http://www.sciencedirect.com/science/article/pii/S1364032108001664.

Hain, J.J. et al., 2005. Additional renewable energy growth through small-scale community orientated energy policies. *Energy Policy*, 33(9), pp.1199–1212. Available at: http://www.sciencedirect.com/science/article/pii/S0301421503003562.

Hallam, C.R.A. & Contreras, C., 2015. Evaluation of the levelized cost of energy method for analyzing renewable energy systems: A case study of system equivalency crossover points under varying analysis assumptions. *Systems Journal, IEEE*, 9(1), pp.199–208.

Hanley, N. & Nevin, C., 1999. Appraising renewable energy developments in remote communities: the case of the North Assynt Estate, Scotland. *Energy Policy*, 27(9), pp.527–547. Available at: http://www.sciencedirect.com/science/article/pii/S0301421599000233.

IEA, 2010. *World Energy Outlook 2010*, Paris. Available at: http://www.smithschool.ox.ac.uk/wp-content/uploads/2010/06/Fatih-Birol.pdf [Accessed February 19, 2013].

Indradip, M., 2006. A renewable island life: Electricity from renewables on small islands. *Refocus*, 7(6), pp.38–41. Available at: http://www.sciencedirect.com/science/article/pii/S1471084606706588.

IPCC, 2011. *Special Report on Renewable Energy Sources and Climate Change Mitigation.* O. Edenhofer et al., eds., United Kingdom and New York, NY, USA: Cambridge University Press.

Jackson, T. & Surrey, G., 2005. Motivating Sustainable Consumption: a review of evidence on consumer behaviour and behavioural change. *A report to the Sustainable Development Research Network*. Available at: https://www.c2p2online.com/documents/MotivatingSC.pdf.

Jones, C.R. & Richard Eiser, J., 2010. Understanding "local" opposition to wind development in the UK: How big is a backyard? *Energy Policy*, 38(6), pp.3106–3117. Available at: http://www.sciencedirect.com/science/article/pii/S0301421510000790.

Kaldellis, J.K. & Zafirakis, D., 2007. Present situation and future prospects of electricity generation in Aegean Archipelago islands. *Energy Policy*, 35(9), pp.4623–4639. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421507001425 [Accessed

February 19, 2013].

Kaldellis, J.K., Zafirakis, D. & Kavadias, K., 2009. Techno-economic comparison of energy storage systems for island autonomous electrical networks. *Renewable and Sustainable Energy Reviews*, 13(2), pp.378–392. Available at: http://www.sciencedirect.com/science/article/pii/S1364032107001475.

Kanase-Patil, A.B., Saini, R.P. & Sharma, M.P., 2010. Integrated renewable energy systems for off grid rural electrification of remote area. *Renewable Energy*, 35(6), pp.1342–1349. Available at: http://www.sciencedirect.com/science/article/pii/S0960148109004315.

Kaplan, S., 2000. New Ways to Promote Proenvironmental Behavior: Human Nature and Environmentally Responsible Behavior. *Journal of Social Issues*, 56(3), pp.491–508. Available at: http://dx.doi.org/10.1111/0022-4537.00180.

Kaundinya, D.P., Balachandra, P. & Ravindranath, N.H., 2009. Grid-connected versus stand-alone energy systems for decentralized power - A review of literature. *Renewable and Sustainable Energy Reviews*, 13, pp.2041–2048.

Kellett, J., 2007. Community-based energy policy: A practical approach to carbon reduction. *Journal of Environmental Planning and Management*, 50(3), pp.381–396. Available at: http://dx.doi.org/10.1080/09640560701261679.

Krajačić, G. et al., 2011. Planning for a 100% independent energy system based on smart energy storage for integration of renewables and CO2 emissions reduction. *Applied Thermal Engineering*, 31(13), pp.2073–2083. Available at: http://www.sciencedirect.com/science/article/pii/S1359431111001463 [Accessed February 19, 2013].

Mcewen, N. et al., 2012. *A Report on Community Renewable Energy in Scotland - SCENE Connect Report*, Available at: http://library.uniteddiversity.coop/REconomy_Resource_Pack/Community_Energy/A_report_on_Community_Energy_in_Scotland.pdf.

Mendes, G., Ioakimidis, C. & Ferrao, P., 2011. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. *Renewable and Sustainable Energy Reviews*.

Michalena, E. & Angeon, V., 2009. Local challenges in the promotion of renewable energy sources: The case of Crete. *Energy Policy*, 37(5), pp.2018–2026. Available at: http://www.sciencedirect.com/science/article/pii/S030142150900069X.

Muller, M.O. et al., 2011. Energy autarky: A conceptual framework for sustainable regional development. *Energy Policy*, 39(10), pp.5800–5810. Available at: http://www.sciencedirect.com/science/article/pii/S0301421511003028.

Nair, N.-K.C. & Garimella, N., 2010. Battery energy storage systems: Assessment for small-scale renewable energy integration. *Energy and Buildings*, 42(11), pp.2124–2130. Available at: http://www.sciencedirect.com/science/article/pii/S0378778810002185.

Nkwetta, D.N. & Haghighat, F., 2014. Thermal energy storage with phase change material—a state-of-the art review. *Sustainable Cities and Society*, 10, pp.87–100.

NREL, HOMER Energy. Available at: http://homerenergy.com/.

Ntziachristos, L. et al., 2005. A wind-power fuel-cell hybrid system study on the non-interconnected Aegean islands grid. *Renewable Energy*, 30(10), pp.1471–

1487. Available at: http://www.sciencedirect.com/science/article/pii/S0960148104004252.

Ofgem, 2012. *Electricity Capacity Assessment*, Available at: http://www.ofgem.gov.uk/Markets/WhlMkts/monitoring-energy-security/elec-capacity-assessment/Documents1/Electricity Capacity Assessment 2012.pdf.

Padrón, S., Medina, J.F. & Rodríguez, a., 2011. Analysis of a pumped storage system to increase the penetration level of renewable energy in isolated power systems. Gran Canaria: A case study. *Energy*, 36(12), pp.6753–6762. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0360544211006888 [Accessed February 6, 2013].

Prodromidis, G.N. & Coutelieris, F.A., 2010. A comparative feasibility study of stand-alone and grid connected RES-based systems in several Greek Islands. *Renewable Energy*, 36(7), pp.1957–1963. Available at: http://www.sciencedirect.com/science/article/pii/S0960148110005756.

Raccichini, R. et al., 2015. The role of graphene for electrochemical energy storage. *Nature materials*, 14(3), pp.271–279.

Rae, C. & Bradley, F., 2012. Energy autonomy in sustainable communities - A review of key issues. *Renewable and Sustainable Energy Reviews*, 16(9), pp.6497–6506. Available at: http://www.sciencedirect.com/science/article/pii/S1364032112004716.

Rae, C. & Bradley, F., 2013. The Emergence of Low Carbon Energy Autonomy in Isolated Communities. *Journal of Technology Innovations in Renewable Energy*, 2(3), pp.205–221. Available at: http://www.lifescienceglobal.com/home/cart?view=product&id=726.

Ren, L. et al., 2012. Techno-economic evaluation of hybrid energy storage technologies for a solar-wind generation system. *Physica C: Superconductivity*, (0). Available at: http://www.sciencedirect.com/science/article/pii/S0921453412000998.

REN21, 2015. *Renewables 2016: Global Status Report*, Available at: http://www.ren21.net/status-of-renewables/global-status-report/.

del Rio, P. & Burguillo, M., 2008a. An empirical analysis of the impact of renewable energy deployment on local sustainability. *Renewable and Sustainable Energy Reviews*, 13(6-7), pp.1314–1325. Available at: http://www.sciencedirect.com/science/article/pii/S1364032108001044.

del Rio, P. & Burguillo, M., 2008b. Assessing the impact of renewable energy deployment on local sustainability: Towards a theoretical framework. *Renewable and Sustainable Energy Reviews*, 12(5), pp.1325–1344. Available at: http://www.sciencedirect.com/science/article/pii/S1364032107000433.

Rogers, J.C. et al., 2008. Public perceptions of opportunities for community-based renewable energy projects. *Energy Policy*, 36(11), pp.4217–4226.

Roseland, M., 2000. Sustainable community development: integrating environmental, economic, and social objectives. *Progress in Planning*, 54(2), pp.73–132. Available at: http://www.sciencedirect.com/science/article/pii/S0305900600000039.

Scottish Government, 2014. *Community Energy Policy Statement (Draft for public consultation)*, Edinburgh. Available at: http://www.scotland.gov.uk/Resource/0045/00457876.pdf.

Scottish Government, Renewable Energy for Communities. Available at: http://www.gov.scot/Topics/Business-Industry/Energy/Energy-sources/19185/Communities.

Shamsuzzoha, A.H.M., Grant, A. & Clarke, J., 2011. Implementation of renewable energy in Scottish rural area: A social study. *Renewable and Sustainable Energy Reviews*.

Singal, S.K., Varun & Singh, R.P., 2007. Rural electrification of a remote island by renewable energy sources. *Renewable Energy*, 32(15), pp.2491–2501. Available at: http://www.sciencedirect.com/science/article/pii/S0960148107000079.

Sorensen, B., 2011. *Renewable Energy: Physics, Engineering, Environmental Impacts, Economics & Planning.*, Elsevier.

Strong, L. & Which?, 2014. Wrestling with trust. In *Energy Systems Conference 2014*.

The World Bank, 2011. Urban Population (% of total). , 2012(11th December). Available at: http://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS/countries/1W?display=graph.

UK Green Investment Bank, UK Green Investment Bank. Available at: http://www.bis.gov.uk/greeninvestmentbank.

Underwood, C.P. et al., 2007. Renewable-energy clusters for remote communities. *Applied Energy*, 84(6), pp.579–598. Available at: http://www.sciencedirect.com/science/article/pii/S0306261907000219.

Walker, G. et al., 2007. Harnessing community energies: explaining and evaluating community-based localism in renewable energy policy in the UK. *Global Environmental Politics*, 7(2), pp.64–82.

Walker, G., 2008. What are the barriers and incentives for community-owned means of energy production and use? *Energy Policy*, 36(12), pp.4401–4405. Available at: http://www.sciencedirect.com/science/article/pii/S0301421508004576.

Walker, G. & Devine-Wright, P., 2008. Community renewable energy: What should it mean? *Energy Policy*, 36(2), pp.497–500. Available at: http://www.sciencedirect.com/science/article/pii/S0301421507004739.

Warren, C.R. & McFadyen, M., 2010. Does community ownership affect public attitudes to wind energy? A case study from south-west Scotland. *Land use policy*, 27(2), pp.204–213. Available at: http://www.sciencedirect.com/science/article/pii/S0264837709000039.

Willis, R., 2006. Grid 2.0: the next generation. *Green Alliance, London*.

Wrigley, E.A., 2013. Energy and the English Industrial Revolution. *Philisophical Transactions of the Royal Society*, (January). Available at: http://rsta.royalsocietypublishing.org/content/371/1986/20110568.short.

Xu, J., Wang, R.Z. & Li, Y., 2014. A review of available technologies for seasonal thermal energy storage. *Solar Energy*, 103, pp.610–638.

Young, D.C., Mill, G.A. & Wall, R., 2007. Feasibility of renewable energy storage using hydrogen in remote communities in Bhutan. *International Journal of Hydrogen Energy*, 32(8), pp.997–1009. Available at: http://www.sciencedirect.com/science/article/pii/S0360319906002825.

Zoulias, E.I. & Lymberopoulos, N., 2007. Techno-economic analysis of the integration of hydrogen energy technologies in renewable energy-based stand-alone power systems. *Renewable Energy*, 32(4), pp.680–696. Available at: http://www.sciencedirect.com/science/article/pii/S0960148106000620.

Chapter 3: Domestic Energy Consumption and Demand Response

3.1 Domestic Energy Consumption

As discussed in the previous chapter, the realisation of more sustainable and renewable energy systems requires not only a shift in the way energy is generated, stored and distributed, but also in the manner in which it is consumed. And with domestic energy consumption accounting for around 27% of the UK's total energy consumption, the level of analysis into the way energy is consumed in the home has never been more detailed (DECC 2014). Indeed, when electricity consumption is viewed separately the domestic sector's share is even higher, accounting for around 38% of the UK's total electrical consumption (DECC 2015).

3.1.1 Factors affecting domestic energy consumption

Domestic energy consumption is therefore an area of some significance within the wider energy debate and an important factor within the transition towards a more sustainable energy supply model. Aside from its obvious relevance and potential impact on overall energy consumption, there are two additional reasons which ensure that domestic energy consumption remains an area of significant and ongoing research interest: the complexity associated with domestic consumption, and the fact that societal and technological trends continually evolve.

As the understanding of the factors affecting domestic consumption have improved, so too have the approaches taken to try and explain it. Traditionally, a more technological approach towards understanding domestic consumption has been favoured, which involved the analysis of a number of physical and technical factors which are comparatively easy to quantify. And whilst understanding has evolved to include a wider range of ‘softer’ factors (discussed below) these ‘hard’ factors remain significant.

The first and perhaps most obvious of these ‘hard’ factors relates to the way in which domestic consumption can vary according to the physical characteristics of the household itself. An investigation into the impact of these physical characteristics was conducted by (Yohanis et al. 2008), who studied a number of factors including dwelling type, location, size, occupancy (including the age and income of occupants) and appliance usage whilst examining domestic demand. These parameters were found to have differing impacts on overall levels of consumption.

In attempting to compare the impact of increased building envelope thermal efficiency with that of behavioural change, (Schweiker & Shukuya 2010) found that external temperature also had a significant bearing on domestic consumption via its influence on the demand for space heating and cooling. This confirms that domestic consumption also varies according to geographical location.

In addition to the ‘hard’ factors discussed above, recent decades have seen greater recognition of the importance of ‘soft’ factors, which includes a wide range of factors from the fields of economics and behavioural science. This increasingly broad-ranging approach has significantly increased the apparent complexity of the subject when compared to the approach centred on ‘hard’ factors.

The need to combine both ‘hard’ and ‘soft’ approaches was identified most notably by (Hitchcock 1993), and later by (Keirstead 2006) and (Faiers et al. 2007). Faiers et al. identify a list of relevant theories and models which relate to the following broad areas:

- consumer choice
- needs, values and attitudes
- individual learning
- social learning
- the buying process
- the categorisation of consumers and products/appliances

Each of these broad areas are in themselves distinct and wide-ranging bodies of theory which have been developed over time. This demonstrates the breadth of the field, and illustrates the complexity associated with fully understanding domestic consumption.

This increasingly multi-disciplinary approach has succeeded in broadening understanding of the subject and, as noted by (Owens & Driffill 2008), has helped to identify ways in which energy consumption can be influenced and managed. This will be discussed in more detail in section 3.2.

Of the softer factors listed above, one which is particularly important to consider is the cost of energy, which has been following a generally rising trend in recent years, despite a number of short term fluctuations (not least that which occurred in 2015 and early 2016). Figure 3-1 shows the increase in UK domestic energy prices since 1970 (corrected for inflation).

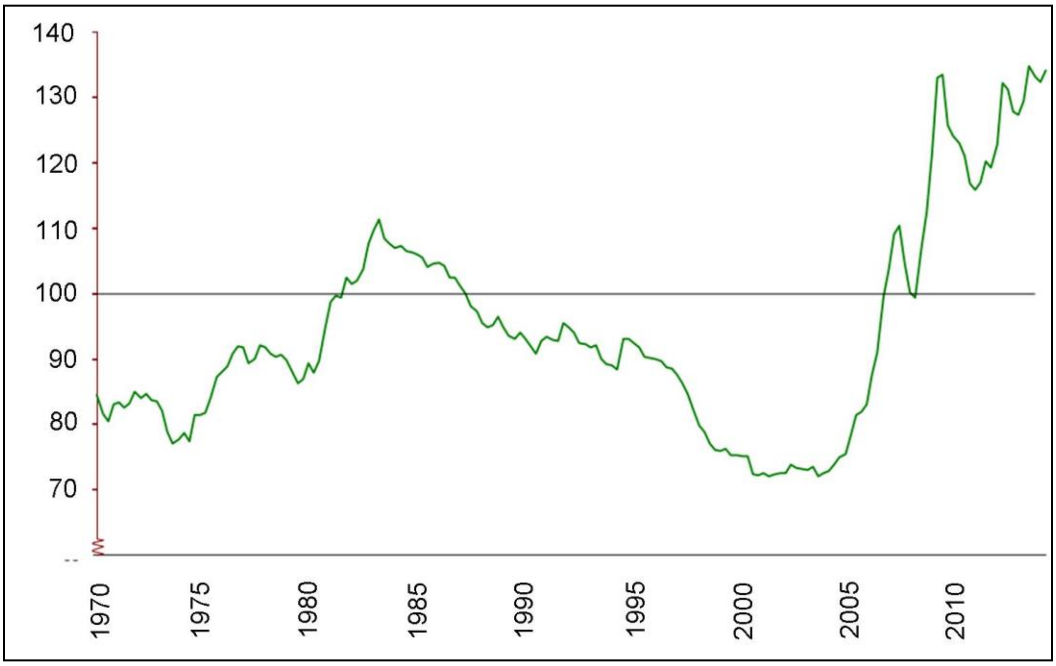


Figure 3-1 - Index of UK domestic fuel price since 1970 (Index 1987 = 100). Source:(DECC 2013).

As a result, energy prices are the subject of much debate, with regulator Ofgem playing an increasingly active role in maintaining transparency, fairness and value for money for the customer (Ofgem 2014a). The rapid price increase which has occurred over the last decade can be seen to expedite the transition towards a more affordable and sustainable energy model. The price of energy also has a direct knock-on effect on the amount of household income which goes towards energy consumption. (Druckman & Jackson 2008) investigated the link between deprivation and domestic consumption and found a strong link between the two, with households in the most deprived areas of society consuming less energy than those in less deprived areas, whilst simultaneously spending a greater proportion of their household income on energy. (Black et al. 1985) also found evidence to suggest that rising fuel prices were more likely to result in “economic sacrifices” than energy savings.

The behavioural aspects of domestic energy consumption are discussed in more detail in section 3.2.4.

3.1.2 Historical and emerging trends

As discussed above, domestic energy consumption (and the factors which influence it) is a complex phenomenon, making it difficult to fully understand. However, examining historic consumption data allows for the identification of key trends and issues which play an important role. The analysis of energy consumption data (including that associated with other sectors such as transport, industry and commerce) therefore plays an important role in the understanding of consumption behaviour and the prediction of likely future trends and their impact on how energy is generated and distributed (Pérez-Lombard et al. 2008).

Since 1970, the amount of energy consumed by households in the UK has grown by 17% - an average of 0.4% per year (Palmer et al. 2011). However, during this time the number of households in the UK has increased by around 40%, whilst average household sizes have decreased. It is therefore thought that whilst consumption has increased, the amount of energy being consumed by the average home has fallen by around 16% since 2000 (DECC 2014).

The nature of these changes can be better understood by examining the breakdown of domestic consumption into major appliance types. Figure 3-2, published by the UK Department for Energy and Climate Change (DECC) breaks down overall UK domestic electrical consumption into six main appliance types. This allows historic trends to be identified, such as the impact of efficiency improvements in both cold appliances and lighting. Also clearly identifiable is the rapid increase in consumption associated with home computing appliances, with consumption from consumer electronics alone thought to have increased by 77% since 1990, with around two thirds of this increase occurring since 2000 (DECC 2014).

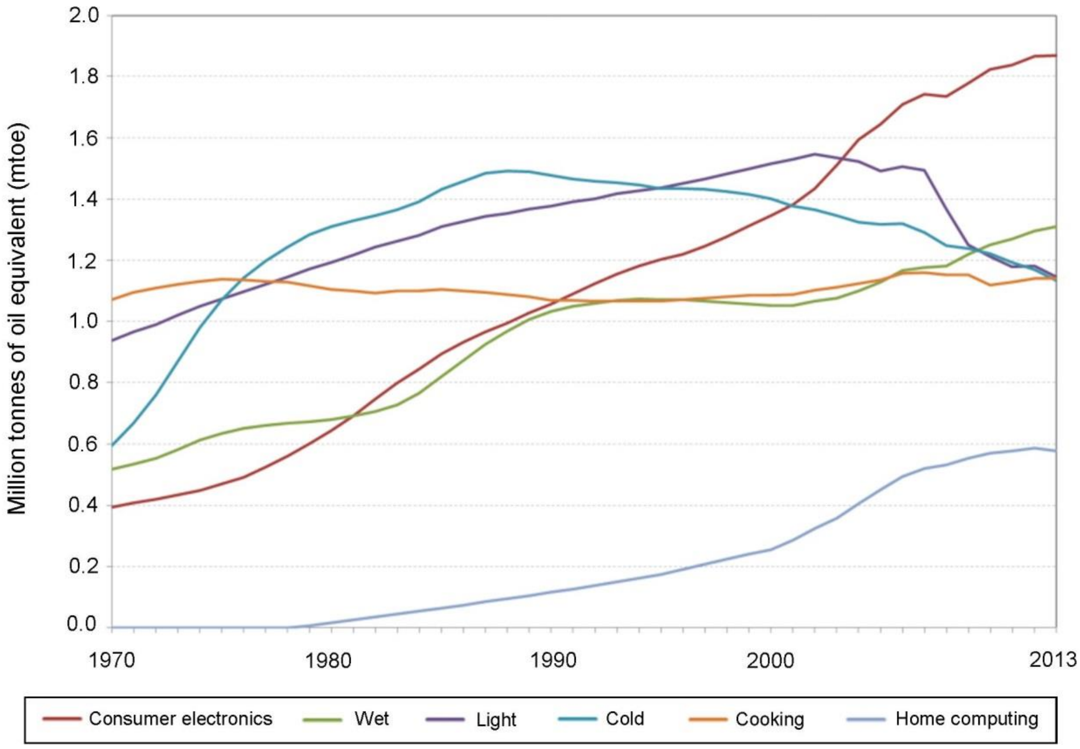


Figure 3-2 - Graph showing UK domestic consumption of various appliance groups since 1970. Source: (DECC 2014).

As a result of this increase, electrical loads now account for over a fifth of domestic electrical demand, with standby consumption accounting for 11% of total consumption (de Almeida et al. 2011). This rise in the use of appliances which continue to consume energy even when not in use (so-called 'standby' consumption) was identified by (Firth et al. 2008) as a key contributor to increases in domestic energy consumption, along with the rise in the use of so-called 'active' appliances such as lighting, kettles and electric showers.

Further study of domestic appliance usage is provided by (Zimmermann et al. 2012), who provide an in-depth analysis of the appliance use information gathered as part of a major survey of domestic electrical consumption carried out by DECC, the Department for Environment, Food and Rural Affairs (DEFRA) and the Energy Saving Trust. Similarly, the Building Research Establishment (BRE) has also used a disaggregated view of energy demand to identify the loads and appliances which contribute towards peak demands (BRE 2008). They identify catering and consumer electronics loads as potentially significant sources of demand reduction.

Recent years have also seen a shift in the consumption of energy by fuel type. In 1970, 39% of domestic energy consumption was coal, with 24% natural gas and 18% electricity. In 2014 however, just 1% of consumption was from coal, with 63% natural gas and 25% electricity (DECC 2014). As well as highlighting the extent of the shift from coal to natural gas, these figures show a significant increase in the role of electricity consumption in the overall energy picture. This is further illustrated by Ofgem's revised estimates of average annual household consumption, which have recently been updated (Ofgem 2011). Table 3-1 shows the differences between the new figures (revised in 2011) and the previous figures, which were derived in 2003.

Table 3-1 - Average annual household energy consumption estimates by fuel type (Source: (Ofgem 2011)).

Household consumption level	Gas (kWh/yr)			Electricity (kWh/yr)		
	2003	2011	Change (%)	2003	2011	Change (%)
Low	10000	11000	10%	1650	2100	27%
Medium	20500	16500	-20%	3300	3300	0%
High	28000	23000	-18%	4600	5100	11%

These changes raise a number of interesting issues. Firstly, the amount of gas thought to be consumed by 'medium' and 'high' level households has been reduced significantly, whilst the estimate for 'low' consumption households has increased. Ofgem attribute the reductions to the recent uptake of a range of energy efficiency measures such as home insulation, the use of efficient boilers and double glazing. However, no explanation is offered as to the cause of the increase in consumption in households within the 'low' consumption bracket. This could be attributed to the fact that some households may not be able to afford the above energy efficiency measures (despite a number of government schemes aimed at improving their affordability). When it comes to electricity, both ‘low’ and ‘high’ consumption brackets have seen significant increases. This has been attributed to an increase in the use of “energy-hungry gadgets” found in typical households, giving further evidence of the impact of increasing appliance ownership on household consumption.

These findings illustrate the emergence of an interesting dynamic, whereby the increase in energy consumption associated with household appliances (and consumer electronics in particular) can be seen to place more stress on the existing energy infrastructure, whilst simultaneously increasing the number of loads which could be used to enact DR, and therefore the ability of households to reduce system stresses.

According to projections made by (BRE 2008), domestic energy consumption appears set to continue decreasing gradually until 2030, before increasing again to 2050. BRE attribute this long term rise in consumption to increased demand for cooling, computers and other electronics. However, this headline projection can be seen to be misleading, as it does not reflect the anticipated changes in the *nature* of domestic electricity consumption - namely the continued increase in appliance ownership and the increasing electrification of domestic energy consumption in general.

Another comparatively recent but potentially significant development is the projected increase in ownership (and in particular the potential domestic overnight charging) of Plug-in Hybrid Electric Vehicles (PHEV’s). The introduction of the widespread use of PHEV’s (should it materialise) would see the addition of a vast number of new and significant loads to domestic sector consumption, and could fundamentally change the nature of domestic consumption. As such, PHEV’s are the subject of a wide range of current research, as summarised by (Huang & Infield 2010). Given the potential scale of the impact of PHEV's on the energy supply model, and the level of uncertainty which exists surrounding their development and future ownership rates, PHEV's have been omitted from the scope of this project.

3.1.3 Modelling domestic energy consumption

Recent developments in the understanding of the various drivers and influences behind domestic energy consumption has in turn facilitated the development of more accurate and sophisticated ways of predicting future consumption and the impact of certain technical and social interventions. This is achieved in large part through the use of modelling - a process which sees a mathematical or conceptual representation of a real-life entity developed, in order to allow inferences to be drawn about possible future changes to that entity (Sargent 2005).

The methods used to model energy demand are many and varied, but generally fall into two main approaches: top-down and bottom-up. As illustrated by Swan and Ugursal in their comprehensive review, each approach has its own particular merits and applications to which it is best suited (Swan & Ugursal 2009).

The top-down approach involves taking large data sets (such as national or regional-scale survey or statistical data) and breaking down the whole in order to gain insight into each of the constituent parts. This approach is useful in the identification of long term trends, and in drawing general conclusions when the level of information available is low. One such example is the United States Energy Information Administration's National Energy Modelling System Residential Demand Module (International Energy Administration 2013), which is used to generate long-term (in this case to 2040) projections of domestic energy use in order to inform policy decisions. Given the broad applicability of such a model the level of information generated is understandably broad, with the identification of wide ranging, long-term trends favoured over highly detailed output.

Given the increasingly detailed analysis of domestic consumption which has taken place in recent years, it is no surprise that the number of models which utilise the bottom-up approach has also increased (Yao & Steemers 2005; Borg & Kelly 2011; Capasso et al. 1994; Richardson et al. 2010; Widén et al. 2009). This approach involves the aggregation of information from a variety of smaller sources, with a view to drawing conclusions on the wider system as a whole, as demonstrated by (Borg & Kelly 2011). This approach has been facilitated by the increasing accuracy of data capture and logging, often in the form of high resolution metering (discussed in more detail later in this chapter). Consumer surveys have also been used to collate large quantities of highly detailed information, which can also be used to great effect, as demonstrated by the Energy Follow-up Survey conducted by DECC and BRE in 2011 (DECC & BRE 2013). This level of detail makes the bottom-up approach more suitable for assessing the likely impacts of small changes to consumption, such as behavioural and technological interventions, and favours accuracy over the identification of long-term trends.

One particularly effective demonstration of the applications of the bottom-up approach is provided by (Richardson et al. 2010), who combine appliance usage figures with a statistical approach to modelling household occupancy in order to create a high resolution domestic energy demand model. As pointed out by (Chrysopoulos et al. 2014), such an approach also facilitates the modelling of incremental energy efficiency improvements.

However, given the importance and potential impact of subtle changes in demand, the bottom-up approach is not without criticism. (Natarajan et al. 2011) point to the limitations associated with the deterministic nature of bottom-up modelling, citing the inherently uncertain nature of domestic consumption as a potential source of inaccuracy. (Swan & Ugursal 2009) also identify the failure of bottom-up models to account fully for occupant behaviour, but do however also argue that the use of increasingly accessible appliance level consumption data does enable such models to account more accurately for consumer behaviour than ever before.

3.2 Demand Response and Behavioural Change

Just as the nature of domestic energy consumption is expected to continue to change, the relationship between domestic consumers and their energy supply is also expected to undergo significant change in the coming years, with consumers expected to play an increasingly active role (Gangale et al. 2013; Verbong et al. 2013). This shift from passive consumption to active and more responsive consumption is expected to arise due to a number of factors acting upon both consumers and network operators/energy providers (Albadi & El-Saadany 2008). On the consumer side, it is thought that rising energy bills will promote households to consider their energy consumption behaviour more carefully in order to minimise unnecessary expenditure (US Department of Energy 2006; Kirschen 2003). Simultaneously, on the network side operators are seeking cost-effective ways of managing the amount of stress placed on existing infrastructure, with the promotion of responsive demand being identified as a cost-effective alternative to infrastructure upgrades (Bradley et al. 2013; Strbac 2008). The net result is a shift away from the traditional energy supply model, whereby energy supply is expected to respond to changes in demand, towards a more balanced model in which each responds to signals from the other. The change in this relationship can also be characterised as a strengthening of the perceived link between consumers and their energy supply, resulting in consumers responding to signals from the network as well as vice-versa. By introducing a two-way flow of information between consumers and their network, it is possible for network operators to try and manipulate/encourage certain energy consumption patterns. This involves the stimulation of changes to energy consumption, such as those shown in Figure 3-3. These can be achieved through a combination of load shifting, load curtailment and load growth/extension.

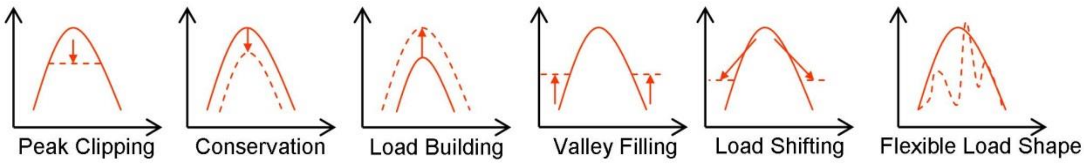


Figure 3-3 - Graphs showing the various desired outcomes of Demand Response.

This is commonly referred to as Demand Response (DR), and is defined by the US Department of Energy as “the alteration of normal energy consumption behaviour by consumers, which occurs in response to changes in energy pricing or other signals” (US Department of Energy 2006). DR is therefore considered an integral part of the transition towards a sustainable energy future, and as such is the subject of extensive research at governmental, industrial and academic levels.

This section provides an overview of the main benefits and drawbacks associated with DR in general, as summarised in Table 3-2. The role of consumers is also discussed, along with the potential for technology to facilitate DR. The implementation of DR schemes in the domestic sector, and in particular the use of variable energy pricing, will be discussed in more detail in the following chapter.

Table 3-2 - Summary of potential benefits and barriers/drawbacks to DR.

Benefits	Barriers and Drawbacks
Financial savings for consumers, via incentive payments and reduction in bills.	Uncertainty surrounding the best approach to implementation.
Cost-effectiveness of DR in comparison to infrastructure and capacity upgrades.	Influence of non-financial motivating factors on consumption behaviour.
Potential for increased security of supply and network reliability due to the ability to limit/avoid network stresses/constraints.	Lack of consumer knowledge and understanding regarding the need for (and consequences of) DR actions.
Increased utilisation of generation capacity and reduced need for back-up generation.	Regulatory and bureaucratic barriers to the design, testing and regulation of DR.
Increased utilisation of renewable energy.	Resistance to the restructuring of the energy market to better facilitate DR.
Can reduce energy market power.	Potential for failure to deliver perceived benefits (such as those listed opposite).
Can contribute to reducing energy price volatility.	Loss of consumer utility through interruptions to desired patterns of consumption.
	Increased metering and administration costs.

3.2.1 The benefits of DR

The potential scale and scope for domestic DR has been the subject of considerable research and investigation in recent years (Hamidi et al. 2009; DECC, Frontier Economics, et al. 2012; Dupont et al. 2012; McKenna 2013; Gruenewald & Torriti 2014). Given the domestic sector's scale, and the impact it has on cross-sector energy demand as a whole, it is considered to be an area of considerable potential.

The main benefits associated with DR can be split into four main categories, as defined by (Albadi & El-Saadany 2008):

1. Benefits to the participant.
2. Benefits to the wider energy market.
3. Enhanced reliability/security of supply.
4. Improved energy market performance.

The first of these involves the benefits to the participant i.e. the consumer. In most cases, the primary benefit to the consumer comes through the potential reductions in energy bills which are associated with participation in DR schemes (DECC, Frontier Economics, et al. 2012). This is seen as the main incentive for consumers, and is increasingly relevant given the increase in energy bills discussed earlier in this chapter. However, there is also an argument that consumer motivations are likely to include more than just financial factors. Darby is amongst those who argue that over-reliance upon financial motivators results in the neglect of other significant motivating factors, such as pro-environmental attitudes, a sense of community responsibility/duty and behavioural factors which affect consumption (Darby 2006).

As well as creating potential benefits, DR is also said to benefit the energy market as a whole (Albadi & El-Saadany 2008). When compared to often costly infrastructure upgrades DR can represent a more cost-effective method of reducing the stress upon infrastructure. It can also improve the efficiency of the network as a whole, in that it lessens the requirement for reserve generation capacity by increasing the utilisation of existing capacity (Strbac 2008).

Another area where DR could bring potential benefits relates to the reliability and security of energy supply. A more responsive demand profile improves the reliability of the energy system by engaging consumers and helping to avoid power outages and interruptions caused by stress and constraints on the network. While this could be seen to benefit all stakeholders, it is particularly relevant in the remote and isolated areas where existing energy supply infrastructure is weakest.

3.2.2 Drawbacks and barriers to DR

Despite this widely positive view of domestic DR and its potential contribution to the energy market, there remains significant debate and uncertainty as to how best to implement it. This uncertainty serves as a significant barrier, preventing the widespread deployment of DR in the domestic sector. However, it is also indicative of the complexity of the subject, and of the importance of finding an effective approach capable of providing sustained success.

The drawbacks associated with DR and its various methods of implementation are comprehensively reviewed by (Kim & Shcherbakova 2011), who also propose solutions to some long-running barriers to DR. Essentially, the drawbacks associated with DR initiatives can be seen to stem primarily from the failure to deliver their intended benefits, such as those discussed above. But criticism has also been made of the fundamental principles upon which many DR schemes are based.

Kim and Shcherbakova categorise the challenges associated with DR into three mains areas - consumer barriers, producer barriers and structural barriers. Consumer barriers relate to the characteristics and attitudes of consumers which can be seen to impede the implementation of DR. This stems from a lack of basic understanding as to 'where energy comes from', but can also be partially attributed to a lack of appropriate information. Producer barriers relate to factors which limit the desire and ability of energy suppliers and network operators to implement DR initiatives. Finally, structural barriers are those related to the design, implementation and regulation of DR initiatives, and to the associated restructuring of the energy market as a whole.

DR requires a certain level of technology in order to be implemented smoothly and successfully. Until recently, technology which is both capable and affordable has been scarce. This lack of technology is identified as a significant barrier to DR, with Spees and Lave arguing that the lack of sophisticated (i.e. hourly) metering is the single biggest barrier to price-based DR (Spees & Lave 2007). But while some authors, including Kim and Shcherbakova (Kim & Shcherbakova 2011) and more recently Ravindra and Iyer (Ravindra & Iyer 2014) continue to list a lack of available technology as a barrier to DR, recent and ongoing technological developments and pilot studies such as the EcoGrid EU project (Ding et al. 2012), and more generally the roll-out of smart metering, show that this barrier is already being overcome .

A central argument to the debate is the issue of exposing consumers to increased levels of financial risk, and the potential for some to be worse off as a result of the implementation of DR initiatives.

One key area of criticism surrounding DR schemes involves consumer participation, and concerns over the fairness of the allocation of financial rewards and penalties associated with participation (Downing & Icaro Consulting 2009; Allcott & Mullainathan 2010). The implementation and regulation of widespread deployment of DR initiatives would also add significant complexity to the energy market (Hammerstrom & Ambrosio 2007). This is unlikely to be met with enthusiasm amongst consumers, with the complexity of energy tariffs and pricing already the subject of much debate. In the UK in particular, recent calls from the regulator Ofgem for energy supply companies to simplify billing and reduce the number of domestic energy tariffs available could potentially act as a significant barrier to the introduction of even more complex time-based energy pricing tariffs (Ofgem 2014b; Ofgem 2014a). The impact of consumer resistance is likely to be highest in schemes which involve mandatory participation and exposure to varying energy prices. Mandatory consumer participation in schemes which expose consumers to greater financial risks and potentially increased energy bills poses a number of major challenges and has therefore been ruled out of the vast majority of DR schemes to date. This can lead to limitations being placed in the applicability of the results, as only the behaviour of willing participants can be observed, whilst comparatively very little is known about the likely behaviour of unwilling or reluctant participants. Those who have volunteered to take part in such schemes can be seen as being more accepting of the increased exposure to financial risk associated with DR. If DR is to be implemented at a large scale i.e. at a regional or nationwide level, then the main point of interest would not necessarily be the behaviour of consumers who volunteer to take part in DR trial schemes, but the number of consumers who, when asked to take part, refuse. The acceptability or ‘social viability’ of DR is therefore seen as a key issue when considering its wider potential. There is therefore a need for greater insight into the overall levels of consumer willingness to engage in DR schemes of various types.

Sustaining changes in consumption has proved difficult in some instances, even with high levels of consumer willingness. The drop-off in responsiveness, referred to as “response fatigue”, can occur after an initial period of high levels of responsiveness if consumers are not provided with regular, effective prompts, and can result in consumers reverting back to their original consumption patterns. (Darby 2006) cites the need for clear and effective feedback as a means of sustaining changes to consumption behaviour beyond the short-term. It is thought that the use of technology to automate DR could also play a role in sustaining changes in consumption. This topic is discussed in more detail later in this section.

Despite having the potential to provide cost savings to consumers, there is concern amongst some authors that financial savings alone may fail to provide sufficient incentive to motivate some consumer groups into DR (McKenna et al. 2011; Darby & McKenna 2012). And whilst increasing the magnitude of potential financial gains/losses is likely to result in more responsive behaviour, it could also lead to increased levels of financial risk for consumers. There is therefore a balance to be struck in order to find the optimum rate of reward for participation in DR. Understandably, motivation is thought to be higher for consumers who spend the highest percentage of their income on energy, such as low-income households or energy-intensive industries. The same can also be said of consumers who rely on more expensive forms of energy supply. Most significantly for this project, this includes those in remote and isolated communities who rely on costly fuel imports, as discussed in previous chapters.

One unintended consequence of widespread participation in DR schemes is the emergence of the so-called ‘free-rider effect’, whereby some consumers benefit from the implementation of DR initiatives without having to adapt their consumption behaviour in any way. This effect is thought to disincentivise those consumers who are willing to make significant changes to their behaviour, by creating a sense of unfairness which leads to disengagement. As such, discussion of free-riders features prominently in literature (Boardman 2004; Borenstein et al. 2002; Clastres 2011; Downing & Icaro Consulting 2009; Kontogianni et al. 2013; Gillingham et al. 2009).

Producer barriers are those faced by those looking to design and implement DR initiatives, and as a result are primarily financial (Kim & Shcherbakova 2011). Whilst DR is often seen as a more cost-effective alternative to the upgrading of infrastructure or the construction of additional generation capacity, the cost of implementing DR is not insignificant (Albadi & El-Saadany 2007; US Department of Energy 2006). As identified by Wang et al. (Wang et al. 2010), few formalised measures exist which allow producers to recover the cost of implementing DR. This creates uncertainty for potential implementers, and serves as a significant barrier. Kim and Shcherbakova argue that this issue is worsened in situations involving the development of a DR initiative or product which could benefit all consumers and providers, because individual firms are reluctant to invest in initiatives that could directly benefit their competitors.

This raises the complicated issue of which energy market stakeholder should take on the responsibility of promoting and implementing DR. A case could be made for any of the potential candidates: energy suppliers, consumers, policy-makers, regulators etc. However, there appears to be a consensus that the optimum solution would involve a sharing of responsibility as part of a coordinated effort to aid the development of DR (Greening 2010; Albadi & El-Saadany 2008).

Structural barriers to DR are those which relate to the design and detail of DR initiatives themselves. The uncertainty surrounding how best to implement DR is considered a major barrier, with numerous authors stressing the need for regulation and the restructuring of the energy market so that DR can be implemented effectively, since the current structure of the energy market is not considered to be conducive to competition or accessible by small scale participants (Kim & Shcherbakova 2011). One notable attempt to address this is the Ecogrid EU project, a large scale microgrid demonstration project on the Danish island of Bornholm. This project attempts to remove barriers to small scale energy producers by allowing them to participate in a real-time bidless market in an effort to ensure that grid-balancing occurs in as economically efficient a way as possible (Ding et al. 2012).

Many authors also cite a lack of relevant formal regulation as a significant barrier to the implementation of DR (Rae & Bradley 2012a; Darby & McKenna 2012; Owens & Driffill 2008). Without a stable and supportive policy environment and regulatory structure, the development of DR could be at a disadvantage compared to the continuation of the current market structure. The policy and regulatory environment surrounding DR is also intrinsically linked to that of small scale and renewable energy generation, and more specifically its integration into energy networks. (Basu et al. 2011) highlight technology standards, interconnection practices, protection schemes, environmental issues, ancillary services and metering as the key technical challenges facing the development of distributed generation and microgrids. Further, more detailed discussion of the regulatory issues facing microgrids is provided by (Abu-Sharkh et al. 2006).

3.2.3 Feedback and the role of the consumer in future energy systems

As discussed previously, the transition to sustainable communities bridges a broad spectrum of engineering and technical disciplines. However, a technical shift in itself, whilst still crucial, does not guarantee the success of any sustainable community project (Schweizer-Ries & Petra 2008). In fact, consumers can have just as great an impact on the success of a project as the performance of the buildings and energy systems which comprise it. Recent decades have seen an increase in public awareness of sustainability issues, with the responsibility (or rather, the ability to effect change) being passed down from large scale actors such as government and industry towards the individual consumer (Mah et al. 2012). This has placed the consumer in a position of considerable power and influence, especially when it comes to the operation of energy systems, and DR. Improvements in building energy efficiency have also contributed to the growing importance of the user (Pilkington et al. 2011). As building design and regulations continue to strive towards higher energy efficiency and lower levels of energy consumption, the impact of energy wasting user behaviours on overall energy efficiency increases.

A common theme in the literature is the need for education and understanding amongst the general public, as it is central to all the methods of bringing about behavioural change. As such, the need for positive interaction and stakeholder engagement is a common theme throughout the literature (Krajačić et al. 2011; Roseland 2000; Mendes et al. 2011; Moloney et al. 2009; Kaplan 2000). (Mansouri et al. 1996) also suggest that a lack of information regarding the required changes to energy consumption behaviour has contributed to the slow development of domestic DR schemes.

This view is supported in part by (Schweiker & Shukuya 2010), who argue that technological and behavioural improvements should go hand in hand, and demonstrate the effectiveness of user education as an emissions reduction tool. However, (Owens & Driffill 2008) argue that consumer education is likely to be ineffectual at modifying consumption behaviour if it is at odds with other social and cultural norms, thereby stressing the importance of the wider social aspects of energy consumption behaviour.

But if consumers are to play a more active role (through DR) in the operation of their energy systems, then they must first be equipped with the information required to enable them to respond accordingly. And while information alone does not translate into action, DR is almost impossible to achieve without it, as noted by (Darby 2006).

The role of feedback in the facilitation of DR is therefore seen as crucial. (Costanzo et al. 1986) point out that the process of translating information into action on the part of the consumer poses a number of challenges, and stress the importance of the quality of the information provided. The feedback that can be provided to consumers ranges from real-time feedback to the use of informative billing and the supply of annual reports. As discussed by (Wood & Newborough 2007), the various possible approaches to providing feedback can vary in the following key areas:

- Energy units displayed
- The method of displaying information
- The location of displays
- The temporal display of feedback
- Categorisation of feedback supplied

Should any of these be approached in an ineffective manner, then there is a risk of consumers becoming disengaged. The same authors also suggest that allowing consumers to set goals for themselves can also contribute to achieving and sustaining changes to consumption.

The provision of feedback therefore both informs and engages consumers, thereby empowering them to make informed energy consumption decisions. The importance for such engagement is highlighted by (Jain et al. 2012), who found that among similar consumers, energy consumption rose as consumer engagement decreased.

Central to the supply of feedback (both to consumers and to energy system operators) is the deployment of high-resolution energy metering. These ‘smart meters’ have seen a rapid increase in deployment in recent years, often as a result of government initiatives such as that in the UK, which aims to have smart meters installed in all homes and businesses by 2020 (DECC, DCLG, et al. 2012).

The dawn of widespread smart metering has provided access to unprecedented levels of near real-time energy consumption data, and as identified by (Pérez-Lombard et al. 2008), such information can play a key role in furthering our understanding of domestic consumption. (Firth & Palmer 2013) highlighted that this can include information on end-usage, in the form of direct meter readings, additional measurements and dedicated pervasive sensing equipment. The significant learning potential associated with the roll-out of smart metering is also identified by (Stephen & Galloway 2012), who present a method of stratifying data captured through smart metering in order to characterise domestic consumption.

Note: The author’s previous research into the role of consumers in sustainable energy systems was presented at the 22nd International Association of People-Environment Studies conference (Rae & Bradley 2012b).

3.2.4 Behavioural change

Recent decades have found the process of influencing consumer behaviour when it comes to energy consumption to be a highly complex one. This can largely be attributed to the growing appreciation (on the part of both researchers and policy-makers) of the importance of consumer consumption behaviour, and what influences it.

With the growing awareness of the importance of the behavioural components of consumption behaviour has come an awareness of the ineffectual nature of previous attempts at promoting behavioural change. As a result, the literature abounds with criticism of past approaches e.g. (Moloney et al. 2009). (Allcott & Mullainathan 2010) are amongst those who identify that much of the research to date has focussed too much on “engineering” and not enough on social science - an approach which they argue could prove to be more cost-effective.

The inclusion of behavioural factors in the study of domestic energy consumption began as recently as the early 1980’s, with (Van Raaij & Verhallen 1983) linking “personal, environmental and behavioural factors” with consumption behaviour and (Heberlein & Warriner 1983) investigating the link between consumer knowledge and attitudes and their propensity for responsive consumption behaviour. Since then, the scope of research into energy consumption behaviour has broadened to include elements of social science, psychological and behavioural economic theory.

Faiers et al. (Faiers et al. 2007) attempt to draw together various theories aimed at understanding domestic consumption behaviour, and identify no less than 27 relevant theoretical areas relating to consumer choice, learning, needs, values and attitudes, social learning, the buying process, the attributes and categorisation of products and the categorisation of consumers. This illustrates the breadth of the field, and the challenges associated with understanding consumer behaviour.

One area which is at the centre of the debate surrounding DR and behavioural change is the apparent over-reliance of current and historic DR initiatives upon financial motivation as a driver of behavioural change. In particular, there is some debate as to whether financial incentive is capable of providing *sustained* behavioural change. Darby (Darby 2006; Darby 2013) is among those who argue that behavioural changes achieved through financial incentives are likely to fade over time if the incentives are removed, and suggests that more sustainable changes to consumption could be achieved through the consideration of a wider range of possible consumer motivations. This call is echoed by (Allcott & Mullainathan 2010) who also argue for the use of non-price based interventions, and by (McKenna et al. 2011) who stress the need for more research into the "human aspect" of DR.

Whilst there are a number of behavioural change theories that attempt to make sense of this most complex issue, each differs in its focus, as explained by (Moloney et al. 2009). The same authors go on to explain that the key distinction in the examination of these models is that which is made between 'internal' and 'external' variables. Internal variables are defined by Moloney et al. as "those that influence or shape what goes on inside a person's mind, such as awareness, knowledge, values, attitudes, behaviour, rational thought processes, emotional states and entrenched habits". External variables are therefore "located in the physical, social and discursive environments in which a person lives". As highlighted by (Jackson & Surrey 2005), the design of many existing and historic DR initiatives is dominated by the 'rational choice model'. This model states that consumers weigh up the benefits and drawbacks of the options available to them, before selecting the option that maximises their benefit. As such, this can be seen as an approach which focuses primarily on internal variables. This assumes that consumers are motivated by self-interest, rational in their behaviour and not influenced by preference or preconceptions. This approach has given rise to the emphasis placed by many on the importance of providing feedback, as discussed in the previous section. However, as Jackson and Surrey point out, the rational choice model fails to account for habit, short-cuts and cues i.e. external variables.

The assumption that consumers will exhibit self-interest in their decision making has also led to criticism (Kaplan 2000). By assuming that consumers behave purely in a self-interested manner, other underlying motivations are neglected, namely altruism, moral obligation/responsibility and aspects of collective decision making. These sources of motivation are more complex and difficult to quantify, given that they are influenced by external factors. However, their influence on consumer consumption behaviour requires that they are included in the debate.

Sheth and Parvatlyar add to the debate by suggesting that consumers exhibit satisficing behaviour when making energy consumption decisions (Sheth & Parvatlyar 1995). This decision making strategy sees consumers settle for a satisfactory outcome as opposed to seeking out an optimum one, and means that consumers are unlikely to pursue changes in, for example, their energy tariff, unless they are dissatisfied with their current arrangements. This is one example of a habitual behaviour, with the transactional cost of potentially marginally beneficial actions providing an element of inertia for consumers (Allcott & Mullainathan 2010).

Another area upon which particular importance is placed by the literature is the influence of social and societal norms. This can be defined as the set of rules which govern the acceptability (or otherwise) of actions and behaviours which exists amongst a group of people or a society. (Allcott & Mullainathan 2010) and (Kaplan 2000) are amongst those who argue that behavioural change is better encouraged through influencing social norms than through appeals to responsibility and altruism. Similarly, (Owens & Driffill 2008) warn that even consumer education is likely to be ineffectual at modifying consumption behaviour if it is at odds with other social and cultural norms.

Traditionally, the design and implementation of DR initiatives has been led by network operators and energy supply companies (ESCOs). However, in recognition of the importance of consumer acceptance and engagement, there has been a concerted effort in recent years to account for consumers' views. This research is exemplified by (Downing & Icaro Consulting 2009), whose work on behalf of the UK Green Building Council and Zero Carbon Hub explores consumer reactions to elements of 'sustainable community infrastructure'. The authors found that while responses towards the subject were generally positive, consumers did have reservations relating primarily to the details of some elements of sustainable community infrastructure. For this reason, it was concluded that consumer attitudes were positive but conditional. Amongst the questions raised, the issue of practicality featured highly, along with concerns about disruptions and outages, and the fairness of the implementation of billing and consumer savings (such as the scope for free-rider behaviour).

As acknowledged by (Owens & Driffill 2008), the increasingly multi-disciplinary approach to understanding consumption behaviour has resulted in a marked increase in the understanding of this most complex phenomenon, and will continue to influence the development of DR initiatives in the future. However, there remains little in the way of consensus as to how best to translate this understanding into the design of DR initiatives. Instead, (Darby 2013) calls for the development of a framework which considers the impact of various forms of DR on consumers, with the intention of providing clarity and support to decision makers.

3.2.5 The role of technology

The diversity in much of the existing research conducted illustrates the many varied approaches to the implementation of DR that are possible. One common theme, however, is the study of how technology can be used to aid in the implementation of DR projects. Whilst not devoid of challenges (as stressed by Saffre and Gedge, 2010 and Torriti et al., 2010 amongst others) the use of technology has in many cases been found to facilitate mutual benefits for both consumers and network operators (Di Giorgio & Pimpinella 2012; Lujano-Rojas et al. 2012; de Almeida et al. 2011; Clastres 2011; Newborough & Augood 1999; Samadi et al. 2010). In their review of 30 major trials of domestic DR schemes, (DECC, Frontier Economics, et al. 2012) found that automation facilitated “the greatest and most sustained household shifts in demand”.

However, uncertainty remains as to how the widespread use of home-automation technology will be received by the general population (Darby 2013). Primarily, this stems from consumer reservations about handing over an element of control to technology.

There are a number of ways in which technology can be used to facilitate DR, and whilst they vary in their application, their aim is the same: to automate the response of the consumer. In doing so, the need for regular, considered engagement from the consumer can be lessened dramatically. The use of technology also enables a greater level of responsiveness to be achieved, by ensuring that automated responses can be made even to relatively insignificant changes in the price or availability of energy which may not elicit a response if they required direct consumer action.

The most common use of technology to automate DR is through direct load control, which involves allowing technology full or partial control over certain loads, so that they can be turned on/off in response to network signals. Most load control approaches involve loads which are largely imperceptible to household occupants, such as electric water heating or thermostat control (Newsham & Bowker 2010; Ericson 2009; Hammerstrom et al. 2007; Chatzivasiliadis et al. 2008). This has been applied in a number of studies, with some success. (Lujano-Rojas et al. 2012) found that an automated domestic load management strategy was capable of achieving a significant reduction in energy bills. Similar results were achieved by (Di Giorgio & Pimpinella 2012) and (Ericson 2009). One particularly prominent field of research in this area centres on the use of an agent-based approach to load control. This approach allows complex behavioural phenomena to be observed among a group of autonomous agents, each behaving according to a set of (often very simple) pre-defined goals or objectives. This has been applied most notably by Dimeas and Hatziargyriou to the field of microgrid control (Aris L Dimeas & Hatziargyriou 2005; A L Dimeas & Hatziargyriou 2005; Dimeas & Hatziargyriou 2009; Chatzivasiliadis et al. 2008; Dimeas & Hatziargyriou 2007). This approach involves defining a number of ‘selling’ and ‘buying’ agents which produce and consume energy, with trades being made between agents according to demand, and facilitated by a central controlling agent. This approach can be used to apply intelligent control to a number of aspects of an energy system, and also allows the behaviour of various stakeholders - who often have conflicting priorities - to be simulated.

The impact of direct load control upon desired or intended energy consumption patterns requires careful consideration (McKenna et al. 2011). Control over the technology and its configuration/programming is typically retained by the utility, though often with a consumer override function. This is obviously an important factor when considering the social viability of the use of load control technologies. So-called ‘smart appliances’ are designed to play a similar role, using in-built load control and load scheduling (Ozturk et al. 2013). As highlighted by (Samadi et al.

2010), there is also scope for the technological and behaviour approaches to further integrate, by allowing the user to configure technological responses, thereby maintaining control over consumption and limiting any negative impact or loss of utility which may otherwise occur.

The potential for DR using technological approaches such as these are considered to be significant. Perhaps crucially though, such an approach is not reliant upon behavioural change as it can be seen to bypass the consumer. (Kupzog & Pollhammer 2009) identify considerable potential for consumer bypass in their discussion of the future role of “active buildings”. However, as discussed by (Darby & McKenna 2012) and (de Almeida et al. 2011), a combination of active consumer response and technologically automated response is considered optimum. The rate of development that related technologies have seen in recent years means that many of the traditionally quoted challenges associated with its use are no longer applicable. Indeed, (Borenstein et al. 2002) even argue that the evaluation of historic attempts to automate DR may well result in an underestimation of its current and future capabilities.

Nevertheless, despite the ever-increasing capability and affordability of automation technology, there are a number of limitations identified in the literature. The first of these relates to the extent to which technology can be effectively deployed. (McKenna et al. 2011) highlight the difficulties in extending the deployment of automation technology beyond low impact loads such as hot water storage heaters, low impact thermostat control etc. The limited scope for appliance level control is also noted by (Dupont et al. 2012), with disruption to consumer behaviour a major limiting factor. In this regard, the scope for the roll-out of technology does appear to be limited, with many other household loads either requiring consumer scheduling and input, or being deemed as inflexible. The suitability of household loads for inclusion in DR will be discussed in more detail in Chapter 6.

3.3 Demand Response in Stand-Alone Energy Systems

The discussion above has focussed on the impact of DR on domestic energy consumption in conventional energy systems. This focus reflects that of the literature, with little in the way of discussion of the potential applications of DR in SAHES. This can be attributed to the fact that DR in a domestic context is still in its infancy. However, as identified by (McKenna et al. 2011), the use of DR within stand-alone applications is nevertheless regarded as an area of significant potential given the potential benefits which it could bring.

Despite being based on the same principles, DR in SAHES can be seen as a fundamentally different proposition to its use in conventional, grid-connected applications. This is because the desired outcomes are also fundamentally different. As discussed above, the overriding aim of DR in conventional applications i.e. where it is applied over a large number of consumers and within a regional/national scale energy system, is to reduce peak demand and reduce the amount of variation in demand which occurs over the course of a day. This in turn brings with it a variety of aforementioned benefits, both to consumers and to system operators. However, given the prominence of intermittent forms of generation in SAHES, this ‘flattening’ of the demand curve has far less benefit, since the ‘supply curve’ itself is less likely to be as flat as a system reliant on dispatchable generation. Instead, the primary aim of DR within SAHES is to improve the demand-supply match.

3.3.1 Challenges and opportunities

The most significant challenges associated with the use of DR schemes within SAHES stem from the inherently uncertain and stochastic nature of renewable energy supply. This requires short time-step response, which represents a far greater need for timely engagement on the part of consumers than in more conventional, grid-connected applications. However, as discussed previously this can be facilitated to a significant extent using technology to automate response.

The inherently uncertain nature of many renewable energy supply technologies also presents a number of forecasting difficulties, with long-term projections of energy output (which would enable responsive consumers to consider changes to consumption behaviour well in advance) being near-impossible to make with any significant accuracy. However, this is a field which continues to develop at pace as more is learned about forecasting, and the long-term performance of renewable energy supply (RES) technologies (Foley et al. 2012).

Predicting demand also presents a number of challenges in SAHES, where the number of consumers is likely to be far smaller than in conventional DR applications. A smaller number of loads means there is likely to be far less load diversity than in applications with larger numbers of participants. This also makes changes in demand more sporadic and susceptible to unforecasted change.

The potential ability of DR to reduce the level of requirement for on-site energy storage (Alam et al. 2013) and back-up generation (and the associated use of fossil fuels) is arguably the greatest opportunity presented by the use of DR in SAHES. This is achieved by increasing the utilisation of renewable energy generators by altering demand to more closely reflect energy generation i.e. demand-supply matching. This again emphasises the importance of the timing of demand, as opposed to peak demand reduction. As such, load shifting is likely to play an even more prominent role in SAHES' DR schemes than it would in more conventional applications, and can help to build demand in order to reduce surplus, as well as reduce it in order to reduce deficit e.g. during periods of low renewable energy output. The potential benefits of demand-supply matching on the viability and operation of SAHES are profound. Energy storage and the use of fossil-fuelled backup generation capacity are two of the most important financial and environmental aspects of many SAHES (Kaundinya et al. 2009). Energy storage in particular has long been considered the 'weak link' in SAHES, due to a combination of efficiency and longevity limitations as well as high capital costs. Therefore, any reduction in the need for energy storage is likely to enhance the financial and technical feasibility of any SAHES.

The aforementioned ability of responsive demand to improve network stability is also particularly relevant in stand-alone systems, where security of supply is considered to be weakest under the prevailing centralised energy supply model. As a result of this, consumers in these areas are considered more likely to be willing to adopt DR practices (either through automation or more directly through behavioural change) in order to facilitate improvements in the reliability and security of their energy supply. As discussed in the previous chapter, and thanks largely to this experience of comparatively poor energy provision, such consumers are also thought to exhibit certain characteristics which have resulted in them serving as ‘early adopters’ when it comes to innovations in energy supply. A similar approach towards alternative and innovative approaches is also therefore likely to be exhibited when it comes to energy consumption. This stems from the assertion that those who are more aware of their energy supply (as a result of historically poor provision, visual reminders, above average energy bills etc.) are more likely to be aware/understanding of the challenges and costs associated with the supply of energy to remote and rural communities. As a result, such consumers can be deemed to be more likely to be amenable to implementing DR.

In their research into the impact of feedback on energy consumption, (Brandon & Lewis 1999) found that people with more pro-environmental attitudes are more likely to change their consumption in response to feedback. Should consumers in SAHES be found to exhibit pro-environmental attitudes, then they can also be considered more likely to exhibit responsive behaviour if they are provided with effective feedback.

3.3.2 From load flattening to demand-supply matching

The fundamental principle of matching energy supply with demand (referred to as ‘demand-supply matching’) lies at the heart of even the most large/complex energy supply network. Central to the challenge of matching demand with supply are the temporal and magnitudinal mismatches that occur between demand and supply, which can be frequent and often unpredictable, particularly when energy supply is inherently uncertain, as with many forms of renewable energy such as wind and solar. This is illustrated in Figure 3-4, which plots the energy output from a building mounted micro wind turbine and the energy demand profile of a small domestic UK property over a 48 hour period.

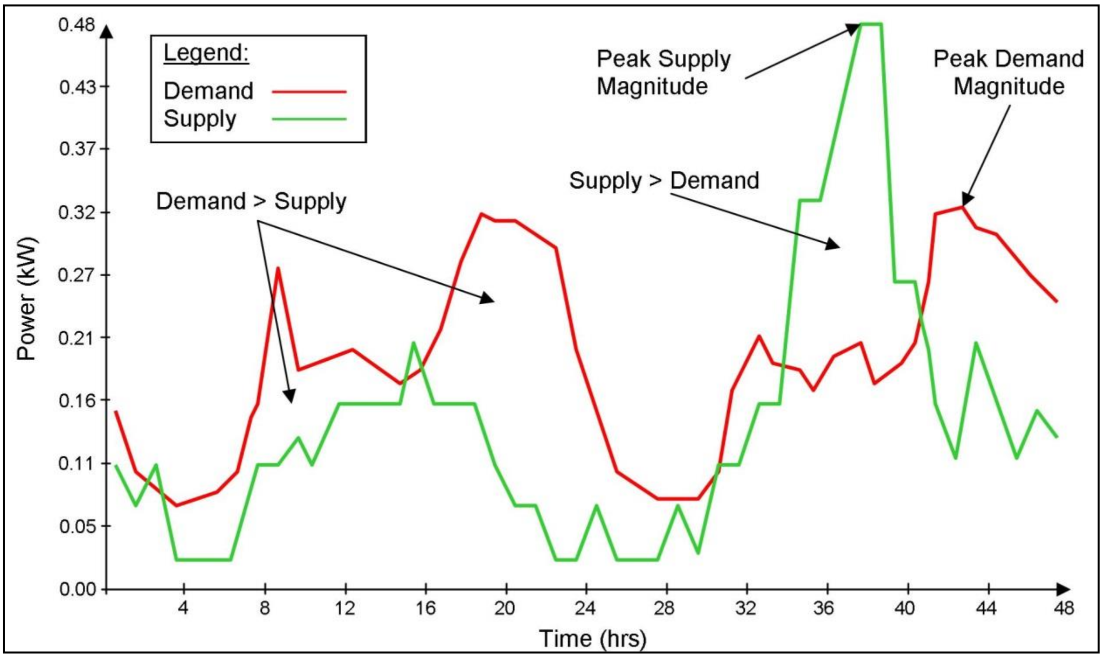


Figure 3-4 - Graph showing fluctuating demand and renewable supply characteristics (from (Rae & Bradley 2012a)).

This graph shows the variations in both demand and supply, and highlights the periods of energy surplus i.e. when supply exceeds demand, and the periods of energy deficit, when demand exceeds supply. This serves to illustrate the importance of energy storage in energy systems which feature significant amounts of renewable generation.

Figure 3-4 also illustrates why the driver of DR in SAHES is demand-supply matching, and not necessarily peak reduction or the flattening of the load profile alone. This requires an approach to DR with a higher temporal resolution than many conventional DR schemes, with sub-hourly response replacing rough time-of-day periods. This involves a greater level of detail, as well demanding increased consumer participation (be it through direct engagement or through automation) and highly accurate metering and control strategies. DR actions within a domestic context will therefore include load growth/extension, load curtailment and load shifting.

3.4 Conclusions

This chapter has reviewed the literature on domestic energy consumption and domestic demand response, and has highlighted some of the key issues surrounding its continued development.

Understanding of the drivers and trends in domestic energy consumption has been expanded in recent decades to include a broader range of socio-economic and behavioural economic factors. This has resulted in a clearer understanding of the factors which affect domestic energy consumption, but crucially has also informed the discussion surrounding how best to elicit changes in consumption behaviour. In particular, there is a growing body of literature which stresses the need for a deeper understanding of consumer attitudes and responses when it comes to DR in the home.

Regardless of the apparent technical and economic feasibility of domestic DR, it cannot be considered truly viable without evidence of support from consumers, and a willingness to engage in such an approach. It is therefore necessary to try and understand consumer attitudes towards DR, so that viable strategies and approaches can be developed.

The literature shows little consensus as to the best approach to effecting behavioural change. This can be attributed to the complexity of the issue, and in particular the range of influencing factors and the fact that attitudes towards energy consumption and demand flexibility are changing constantly. The debate as to how best to promote behavioural change largely centres on whether it is best facilitated by reducing the need for consumer engagement and interaction through automation and the use of ‘smart’ appliances and metering, or whether increased levels of interaction (supported by the education and empowerment of consumers) is more effective.

In order for the true potential of DR to be better quantified, more insight is needed into the overall social viability of DR and the willingness of domestic consumers to accept increased exposure to financial risks and rewards. When it comes to gauging consumer attitudes towards demand flexibility and the scope for significant changes to be made to domestic consumption behaviour, the literature is inconclusive. This is perhaps unsurprising given the inherent complexity associated with what is a highly complex behavioural and socio-economic issue. However, certain key themes are clearly identifiable. Energy systems of the future look set to require greater levels of consumer engagement. This requires a significant degree of behavioural change, which is effectively characterised by the ‘active consumer’ concept. There remains some debate as to how best to achieve the desired changes to consumption behaviour which embody this more active approach to domestic energy demand. The two most common approaches to the subject are the more social, behavioural approach which appeals to consumer motivations and attitudes towards energy consumption, and the more technological approach which facilitates a more passive approach for consumers by using technology to help automate DR. However, it is more likely that the most appropriate approach will combine elements of both approaches.

SAHES are a relatively unexplored area of the field of domestic DR. This can be attributed to the level of complexity associated with DR, which is still to be widely and successfully implemented at a domestic level, even on a grid-connected scale. However, SAHES have been found to differ from more urbanised, grid-connected communities in a number of key areas when it comes to energy consumption and in particular the potential role of DR. The desired outcomes associated with the introduction of DR can also be seen as being fundamentally different within smaller scale, stand-alone energy systems than it is within larger systems, with demand-supply matching taking precedence over the reduction of peak demand.

The attitudes of consumers in remote and rural communities towards DR is in need of further research, and will therefore be investigated in more detail in Chapter 5. The next chapter examines the concept of variable pricing in more detail, and discusses the successes and failures of existing applications. It also discusses the potential role of variable pricing in SAHES.

3.5 References for Chapter 3

Abu-Sharkh, S. et al., 2006. Can microgrids make a major contribution to UK energy supply? *Renewable and Sustainable Energy Reviews*, 10(2), pp.78–127. Available at: http://www.sciencedirect.com/science/article/pii/S1364032104001194.

Alam, M., Ramchurn, S. & Rogers, A., 2013. Cooperative energy exchange for the efficient use of energy and resources in remote communities. In *Autonomous Agents and Multiagent Systems (AAMAS) Conference*. Available at: http://eprints.soton.ac.uk/346637/1/aamas467-alam.pdf [Accessed April 24, 2013].

Albadi, M.H. & El-Saadany, E.F., 2008. A summary of demand response in electricity markets. *Electric Power Systems Research*, 78(11), pp.1989–1996. Available at: http://www.sciencedirect.com/science/article/pii/S0378779608001272.

Albadi, M.H. & El-Saadany, E.F., 2007. Demand response in electricity markets: An overview. In *IEEE power engineering society general meeting*. pp. 1–5.

Allcott, H. & Mullainathan, S., 2010. Behavioral Science and Energy Policy. *Science*. Available at: https://files.nyu.edu/ha32/public/research/Allcott and Mullainathan 2010 - Behavioral Science and Energy Policy.pdf.

de Almeida, A. et al., 2011. Characterization of the household electricity consumption in the EU, potential energy savings and specific policy recommendations. *Energy and Buildings*, 43(8), pp.1884–1894. Available at: http://www.sciencedirect.com/science/article/pii/S0378778811001058.

Basu, A.K. et al., 2011. Microgrids: Energy management by strategic deployment of DERs - A comprehensive survey. *Renewable and Sustainable Energy Reviews*, 15(9), pp.4348–4356. Available at: http://www.sciencedirect.com/science/article/pii/S1364032111003637.

Black, J.S., Stern, P.C. & Elworth, J.T., 1985. Personal and contextual influences on househould energy adaptations. *Journal of Applied Psychology*, 70(1), pp.3–21.

Boardman, B., 2004. New directions for household energy efficiency: evidence from the UK. *Energy Policy*, 32(17), pp.1921–1933. Available at: http://www.sciencedirect.com/science/article/pii/S0301421504000709 [Accessed July 11, 2014].

Borenstein, S., Jaske, M. & Rosenfeld, A., 2002. Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. Available at: http://www.escholarship.org/uc/item/11w8d6m4.

Borg, S.P. & Kelly, N.J., 2011. The effect of appliance energy efficiency improvements on domestic electric loads in European households. *Energy and Buildings*, 43(9), pp.2240–2250. Available at: http://www.sciencedirect.com/science/article/pii/S0378778811001824.

Bradley, P., Leach, M. & Torriti, J., 2013. A review of the costs and benefits of demand response for electricity in the UK. *Energy Policy*, 52, pp.312–327. Available at: http://www.sciencedirect.com/science/article/pii/S0301421512008142 [Accessed December 15, 2015].

Brandon, G. & Lewis, A., 1999. Reducing household energy consumption: a qualitative and quantitative field study. *Journal of Environmental Psychology*, 19(1), pp.75–85.

BRE, 2008. *Final Report: The impact of changing energy use patterns in buildings on peak electricity demand in the UK*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48191/3150-final-report-changing-energy-use.pdf.

Capasso, A. et al., 1994. A bottom-up approach to residential load modeling. *Power Systems, IEEE Transactions on*, 9(2), pp.957–964.

Chatzivasiliadis, S.J., Hatziargyriou, N.D. & Dimeas, A.L., 2008. Development of an agent based intelligent control system for microgrids. In *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*. pp. 1–6. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4596481.

Chrysopoulos, A. et al., 2014. Bottom-up modeling of small-scale energy consumers for effective Demand Response Applications. *Engineering Applications of Artificial Intelligence*, 35, pp.299–315. Available at: http://www.sciencedirect.com/science/article/pii/S0952197614001377

[Accessed September 4, 2014].

Clastres, C., 2011. Smart grids: Another step towards competition, energy security and climate change objectives. *Energy Policy*, 39(9), pp.5399–5408. Available at: http://www.sciencedirect.com/science/article/pii/S030142151100396X.

Costanzo, M. et al., 1986. Energy conservation behavior: The difficult path from information to action. *American psychologist*, 41(5), p.521.

Darby, S., 2006. *The effectiveness of feedback on energy consumption: a review for DEFRA of the literature on metering, billing and direct displays*, Available at: http://powerwatch.biz/site/wp-content/uploads/2012/02/smart-metering-report.pdf.

Darby, S.J., 2013. Load management at home: advantages and drawbacks of some “active demand side” options. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy* , 227 (1), pp.9–17. Available at: http://pia.sagepub.com/content/227/1/9.abstract.

Darby, S.J. & McKenna, E., 2012. Social implications of residential demand response in cool temperate climates. *Energy Policy*, 49(0), pp.759–769. Available at: http://www.sciencedirect.com/science/article/pii/S0301421512006076.

DECC, 2014. *Energy Consumption in the UK (2014) - Chapter 3: Domestic energy consumption in the UK between 1970 and 2013*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/338662/ecuk_chapter_3_domestic_factsheet.pdf.

DECC, 2015. *Energy Trends: June 2015*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/437455/Energy_Trends_June_2015.pdf.

DECC, DCLG, et al., 2012. *Policy paper: 2010 to 2015 government policy: household energy*, UK Government. Available at: https://www.gov.uk/government/publications/2010-to-2015-government-policy-household-energy.

DECC, 2013. *Quarterly Energy Prices: June 2013*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/208286/qep_june_2013.pdf.

DECC & BRE, 2013. *Energy Follow-up Survey 2011 - Report 1: Summary of findings*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/274769/1_Summary_Report.pdf.

DECC, Frontier Economics & Sustainability First, 2012. *Demand Side Response in the domestic sector- a literature review of major trials*, London. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48552/5756-demand-side-response-in-the-domestic-sector-a-lit.pdf.

Dimeas, A.L. & Hatziargyriou, N.D., 2005. A MAS architecture for microgrids control. In *Intelligent Systems Application to Power Systems, 2005. Proceedings of the 13th International Conference on*. p. 5 pp. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1599297&tag=1.

Dimeas, A.L. & Hatziargyriou, N.D., 2009. Control Agents for Real Microgrids. In *Intelligent System Applications to Power Systems, 2009. ISAP ’09. 15th International Conference on*. pp. 1–5.

Dimeas, A.L. & Hatziargyriou, N.D., 2007. Design of a MAS for an Island System. In *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on*. pp. 1–3. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4441679.

Dimeas, A.L. & Hatziargyriou, N.D., 2005. Operation of a Multiagent System for Microgrid Control. *IEEE Transactions on Power Systems*, 20(3), pp.1447–1455.

Ding, Y. et al., 2012. Ecogrid EU – A Large Scale Smart Grids Demonstration of Real Time Market-based Integration of Numerous Small DER and DR. In *2012 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe)*. pp. 1–7.

Downing, P. & Icaro Consulting, 2009. *Understanding Consumer Attitudes to "Sustainable Community Infrastructure,"* Available at: http://www.ukgbc.org/resources/publication/report-understanding-consumer-attitudes-sustainable-community-infrastructure.

Druckman, A. & Jackson, T., 2008. Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy*, 36(8), pp.3177–3192. Available at: http://www.sciencedirect.com/science/article/pii/S0301421508001559 [Accessed December 12, 2014].

Dupont, B., Tant, J. & Belmans, R., 2012. Automated residential demand response based on dynamic pricing. In *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*. pp. 1–7. Available at: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6465806.

Ericson, T., 2009. Direct load control of residential water heaters. *Energy Policy*, 37(9), pp.3502–3512. Available at: http://www.sciencedirect.com/science/article/pii/S0301421509002201 [Accessed August 21, 2015].

Faiers, A., Cook, M. & Neame, C., 2007. Towards a contemporary approach for understanding consumer behaviour in the context of domestic energy use. *Energy Policy*, 35(8), pp.4381–4390. Available at: http://www.sciencedirect.com/science/article/pii/S0301421507000134.

Firth, S. et al., 2008. Identifying trends in the use of domestic appliances from household electricity consumption measurements. *Energy and Buildings*, 40(5), pp.926–936. Available at: http://www.sciencedirect.com/science/article/pii/S0378778807002022.

Firth, S. & Palmer, J., 2013. *Further Analysis of the Household Electricity Use Survey: The Potential for Smart Meters in a National Household Energy Survey*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/275488/smart_meters_and_a_national_energy_survey.pdf.

Foley, A.M. et al., 2012. Current methods and advances in forecasting of wind power generation. *Renewable Energy*, 37(1), pp.1–8.

Gangale, F., Mengolini, A. & Onyeji, I., 2013. Consumer engagement: An insight from smart grid projects in Europe. *Energy Policy*, 60, pp.621–628.

Gillingham, K. et al., 2009. Energy Efficiency Economics and Policy. *Annual Review of Resource Economics*, 1, pp.597–620. Available at:

http://www.nber.org/papers/w15031.pdf.

Di Giorgio, A. & Pimpinella, L., 2012. An event driven Smart Home Controller enabling consumer economic saving and automated Demand Side Management. *Applied Energy*, 96(0), pp.92–103. Available at: http://www.sciencedirect.com/science/article/pii/S0306261912001183.

Greening, L.A., 2010. Demand response resources: Who is responsible for implementation in a deregulated market? *Energy*, 35(4), pp.1518–1525.

Gruenewald, P. & Torriti, J., 2014. Any response? How demand response could be enhanced based on early UK experience. *European Energy Market (EEM), 2014 11th International Conference on the*, pp.1–4.

Hamidi, V., Li, F. & Robinson, F., 2009. Demand response in the UK's domestic sector. *Electric Power Systems Research*, 79(12), pp.1722–1726. Available at: http://www.sciencedirect.com/science/article/pii/S0378779609001710.

Hammerstrom, D. & Ambrosio, R., 2007. *Pacific Northwest GridWise^{TM} Testbed Demonstration Projects; Part 1: Olympic Peninsula Project*, Available at: http://sites.energetics.com/MADRI/toolbox/pdfs/pricing/pnnl_2007_pacific_nw_gridwise_olympic_peninsula.pdf [Accessed August 28, 2013].

Hammerstrom, D.J. et al., 2007. *Pacific Northwest GridWise^{TM} Testbed Demonstration Projects; Part II. Grid Friendly^{TM} Appliance Project*, Pacific Northwest National Laboratory (PNNL), Richland, WA (US). Available at: http://www.pnl.gov/main/publications/external/technical_reports/PNNL-17079.pdf.

Heberlein, T.A. & Warriner, G.K., 1983. The influence of price and attitude on shifting residential electricity consumption from on- to off-peak periods. *Journal of Economic Psychology*, 4(1–2), pp.107–130. Available at: http://www.sciencedirect.com/science/article/pii/016748708390048X.

Hitchcock, G., 1993. An integrated framework for energy use and behaviour in the domestic sector. *Energy and Buildings*, 20(2), pp.151–157.

Huang, S. & Infield, D., 2010. The impact of domestic Plug-in Hybrid Electric Vehicles on power distribution system loads. In *Power System Technology (POWERCON), 2010 International Conference on*. IEEE, pp. 1–7.

International Energy Administration, 2013. *Residential Demand Module of the National Energy Modeling System: Model Documentation 2013*, Washington DC. Available at: http://www.eia.gov/forecasts/aeo/nems/documentation/residential/pdf/m067(2013).pdf.

Jackson, T. & Surrey, G., 2005. Motivating Sustainable Consumption: a review of evidence on consumer behaviour and behavioural change. *A report to the Sustainable Development Research Network*. Available at: https://www.c2p2online.com/documents/MotivatingSC.pdf.

Jain, R.K., Taylor, J.E. & Peschiera, G., 2012. Assessing eco-feedback interface usage and design to drive energy efficiency in buildings. *Energy and Buildings*, 48(0), pp.8–17. Available at: http://www.sciencedirect.com/science/article/pii/S0378778811006499.

Kaplan, S., 2000. New Ways to Promote Proenvironmental Behavior: Human Nature and Environmentally Responsible Behavior. *Journal of Social Issues*, 56(3), pp.491–508. Available at: http://dx.doi.org/10.1111/0022-4537.00180.

Kaundinya, D.P., Balachandra, P. & Ravindranath, N.H., 2009. Grid-connected versus stand-alone energy systems for decentralized power - A review of literature. *Renewable and Sustainable Energy Reviews*, 13, pp.2041–2048.

Keirstead, J., 2006. Evaluating the applicability of integrated domestic energy consumption frameworks in the UK. *Energy policy*, 34(17), pp.3065–3077.

Kim, J.-H. & Shcherbakova, A., 2011. Common failures of demand response. *Energy*, 36(2), pp.873–880. Available at: http://www.sciencedirect.com/science/article/pii/S0360544210007176 [Accessed July 16, 2014].

Kirschen, D.S., 2003. Demand-side view of electricity markets. *Power Systems, IEEE Transactions on*, 18(2), pp.520–527.

Kontogianni, A., Tourkolias, C. & Skourtos, M., 2013. Renewables portfolio, individual preferences and social values towards RES technologies. *Energy Policy*, 55, pp.467–476. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421512010816 [Accessed February 12, 2013].

Krajačić, G. et al., 2011. Planning for a 100% independent energy system based on smart energy storage for integration of renewables and CO2 emissions reduction. *Applied Thermal Engineering*, 31(13), pp.2073–2083. Available at: http://www.sciencedirect.com/science/article/pii/S1359431111001463 [Accessed February 19, 2013].

Kupzog, F. & Pollhammer, K., 2009. Automated buildings as active energy consumers. In *Fieldbuses and Networks in Industrial and Embedded Systems*. pp. 212–217.

Lujano-Rojas, J.M. et al., 2012. Optimum residential load management strategy for real time pricing (RTP) demand response programs. *Energy Policy*, 45, pp.671–679. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421512002248 [Accessed March 9, 2013].

Mah, D.N. et al., 2012. Consumer perceptions of smart grid development: Results of a Hong Kong survey and policy implications. *Energy Policy*, 49, pp.204–216. Available at: http://www.sciencedirect.com/science/article/pii/S0301421512004685 [Accessed July 9, 2014].

Mansouri, I., Newborough, M. & Probert, D., 1996. Energy consumption in UK households: impact of domestic electrical appliances. *Applied Energy*, 54(3), pp.211–285.

McKenna, E., 2013. *Demand response of domestic consumers to dynamic electricity pricing in low-carbon power systems*. Loughborough University. Available at: https://dspace.lboro.ac.uk/2134/12120.

McKenna, E., Ghosh, K. & Thomson, M., 2011. Demand response in low-carbon power systems: a review of residential electrical demand response projects. In *The 2nd International Conference on Microgeneration and Related Technologies*. Glasgow. Available at: http://microgen11.supergen-hidef.org/microgenII/CD/full_papers/p172v2.pdf.

Mendes, G., Ioakimidis, C. & Ferrao, P., 2011. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. *Renewable and Sustainable Energy Reviews*.

Moloney, S., Horne, R.E. & Fien, J., 2009. Transitioning to low carbon communities-from behaviour change to systemic change: Lessons from Australia. *Energy Policy*, 38(12), pp.7614–7623. Available at: http://www.sciencedirect.com/science/article/pii/S0301421509004728.

Natarajan, S., Padget, J. & Elliott, L., 2011. Modelling UK domestic energy and carbon emissions: an agent-based approach. *Energy and Buildings*, 43(10), pp.2602–2612. Available at: http://www.sciencedirect.com/science/article/pii/S0378778811002271.

Newborough, M. & Augood, P., 1999. Demand-side management opportunities for the UK domestic sector. In *IEEE Proceedings - Generation, Transmission & Distribution*. pp. 283–293. Available at: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?tp=&arnumber=790574&contentType=Journals+&+Magazines&sortType=asc_p_Sequence&filter=AND(p_Publication_Number:2195,p_Start_Page:283,p_Issue:3,p_Volume:146).

Newsham, G.R. & Bowker, B.G., 2010. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, 38(7), pp.3289–3296. Available at: http://www.sciencedirect.com/science/article/pii/S0301421510000510 [Accessed July 28, 2014].

Ofgem, 2011. *Factsheet 96: Typical domestic energy consumption figures*, Available at: https://www.ofgem.gov.uk/ofgem-publications/76112/domestic-energy-consump-fig-fs.pdf.

Ofgem, 2014a. Ofgem Simplification Plan 2014-15. , p.16. Available at: https://www.ofgem.gov.uk/ofgem-publications/88528/simplificationplan2014-15.pdf.

Ofgem, 2014b. Simpler Clearer Fairer. *Simpler Clearer Fairer*. Available at: https://www.ofgem.gov.uk/simpler-clearer-fairer [Accessed August 5, 2014].

Owens, S. & Driffill, L., 2008. How to change attitudes and behaviours in the context of energy. *Energy Policy*, 36(12), pp.4412–4418. Available at: http://www.sciencedirect.com/science/article/pii/S030142150800459X.

Ozturk, Y. et al., 2013. An Intelligent Home Energy Management System to Improve Demand Response. *Smart Grid, IEEE Transactions on*, 4(2), pp.694–701.

Palmer, J. et al., 2011. Great Britain's housing energy fact file 2011. *DECC, London*.

Pérez-Lombard, L., Ortiz, J. & Pout, C., 2008. A review on buildings energy consumption information. *Energy and buildings*, 40(3), pp.394–398.

Pilkington, B., Roach, R. & Perkins, J., 2011. Relative benefits of technology and occupant behaviour in moving towards a more energy efficient, sustainable housing paradigm. *Energy Policy*, 39(9), pp.4962–4970.

Van Raaij, W.F. & Verhallen, T.M.M., 1983. A behavioral model of residential energy use. *Journal of Economic Psychology*, 3(1), pp.39–63. Available at: http://www.sciencedirect.com/science/article/pii/0167487083900570.

Rae, C. & Bradley, F., 2012a. Energy autonomy in sustainable communities - A review of key issues. *Renewable and Sustainable Energy Reviews*, 16(9), pp.6497–6506. Available at: http://www.sciencedirect.com/science/article/pii/S1364032112004716.

Rae, C. & Bradley, F., 2012b. The Importance of Human Behaviour in the Success of Sustainable Communities. In *Proceedings of the International Association of*

People-Environment Studies 22nd Conference. Glasgow. Available at: http://iaps.scix.net/cgi-bin/works/Show?iaps_22_2012_2380353_174.

Ravindra, K. & Iyer, P.P., 2014. Decentralized demand–supply matching using community microgrids and consumer demand response: A scenario analysis. *Energy*. Available at: http://www.sciencedirect.com/science/article/pii/S0360544214001777 [Accessed September 3, 2014].

Richardson, I. et al., 2010. Domestic electricity use: A high-resolution energy demand model. *Energy and Buildings*, 42(10), pp.1878–1887. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0378778810001854 [Accessed January 31, 2013].

Roseland, M., 2000. Sustainable community development: integrating environmental, economic, and social objectives. *Progress in Planning*, 54(2), pp.73–132. Available at: http://www.sciencedirect.com/science/article/pii/S0305900600000039.

Saffre, F. & Gedge, R., 2010. Demand-Side Management for the Smart Grid. *Network Operations and Management Symposium Workshops (NOMS Wksps), 2010 IEEE/IFIP*, pp.300–303. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5486558.

Samadi, P. et al., 2010. Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart Grid. *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, pp.415–420.

Sargent, R.G., 2005. Verification and validation of simulation models. In *Proceedings of the 2005 Winter Simulation Conference*. pp. 130–143. Available at: http://delivery.acm.org/10.1145/1170000/1162736/p130-sargent.pdf?ip=130.159.200.13&acc=ACTIVE SERVICE&key=C2716FEBFA981EF1A6C31C7A1C92E751D66EF845E17AF165&CFID=221655955&CFTOKEN=97182266&__acm__=1370270426_25688848375cc5ef5ebdb94713634977.

Schweiker, M. & Shukuya, M., 2010. Comparative effects of building envelope improvements and occupant behavioural changes on the exergy consumption for heating and cooling. *Energy Policy*, 38(6), pp.2976–2986. Available at: http://www.sciencedirect.com/science/article/pii/S0301421510000601.

Schweizer-Ries, P. & Petra, S.-R., 2008. Energy sustainable communities: Environmental psychological investigations. *Energy Policy*, 36(11), pp.4126–4135. Available at: http://www.sciencedirect.com/science/article/pii/S030142150800311X.

Sheth, J.N. & Parvatlyar, A., 1995. Relationship marketing in consumer markets: antecedents and consequences. *Journal of the Academy of marketing Science*, 23(4), pp.255–271.

Spees, K. & Lave, L.B., 2007. Demand Response and Electricity Market Efficiency. *The Electricity Journal*, 20(3), pp.69–85. Available at: http://www.sciencedirect.com/science/article/pii/S1040619007000188 [Accessed November 28, 2014].

Stephen, B. & Galloway, S.J., 2012. Domestic Load Characterization Through Smart Meter Advance Stratification. *Smart Grid, IEEE Transactions on*, 3(3), pp.1571–1572. Available at: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6200414.

Strbac, G., 2008. Demand side management: Benefits and challenges. *Energy Policy*, 36(12), pp.4419–4426. Available at: http://www.sciencedirect.com/science/article/pii/S0301421508004606.

Swan, L.G. & Ugursal, V.I., 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*, 13(8), pp.1819–1835. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1364032108001949 [Accessed March 4, 2013].

Torriti, J., Hassan, M.G. & Leach, M., 2010. Demand response experience in Europe: Policies, programmes and implementation. *Energy*, 35(4), pp.1575–1583. Available at: http://www.sciencedirect.com/science/article/pii/S0360544209002060.

US Department of Energy, 2006. Benefits of demand response in electricity markets and recommendations for achieving them. Available at: http://dandelion-patch.mit.edu/afs/athena.mit.edu/dept/cron/project/urban-sustainability/Old files from summer 2009/Ingrid/Urban Sustainability Initiative.Data/doe_demand_response_rpt_t---ss_feb_17_06_final.pdf.

Verbong, G.P.J., Beemsterboer, S. & Sengers, F., 2013. Smart grids or smart users? Involving users in developing a low carbon electricity economy. *Energy Policy*, 52, pp.117–125.

Wang, J. et al., 2010. Demand response in China. *Energy*, 35(4), pp.1592–1597.

Widén, J. et al., 2009. Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation. *Energy and Buildings*, 41(7), pp.753–768. Available at: http://www.sciencedirect.com/science/article/pii/S0378778809000413.

Wood, G. & Newborough, M., 2007. Energy-use information transfer for intelligent homes: Enabling energy conservation with central and local displays. *Energy and Buildings*, 39(4), pp.495–503. Available at: http://www.sciencedirect.com/science/article/pii/S0378778806002271 [Accessed July 21, 2014].

Yao, R. & Steemers, K., 2005. A method of formulating energy load profile for domestic buildings in the UK. *Energy and Buildings*, 37(6), pp.663–671. Available at: http://www.sciencedirect.com/science/article/pii/S037877880400307X [Accessed July 21, 2015].

Yohanis, Y.G. et al., 2008. Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. *Energy and Buildings*, 40(6), pp.1053–1059. Available at: http://www.sciencedirect.com/science/article/pii/S037877880700223X [Accessed March 3, 2015].

Zimmermann, J.-P. et al., 2012. Household Electricity Survey: A study of domestic electrical product usage. *Intertek Testing & Certification Ltd*.

Chapter 4: Variable Domestic Energy Pricing

4.1 Variable Energy Pricing

This section looks at historic and current examples of variable energy pricing and identifies a number of key issues surrounding its design, implementation and overall potential for success.

The term variable energy pricing refers to pricing tariffs or strategies which involve temporal variations in the price of energy, with the primary aim of promoting change in both the temporal and magnitudinal consumption of energy.

In comparison to commercial and industrial contexts, domestic DR presents a unique challenge in that consumption behaviour is influenced by a broad and complex array of factors. Whilst originally deployed at an industrial scale, there is growing consensus that price-based DR can also be utilised at both commercial and domestic scales (Berry, 1993; Hammerstrom & Ambrosio, 2007; Torriti, Hassan, & Leach, 2010). Such applications have been shown to be successful in many instances (Allcott, 2011; Borenstein, 2005), although the extent of the success that could result from its widespread implementation has been contested, notably by (Lijesen, 2007; Salies, 2013).

4.1.1 The emergence of variable pricing

Variable energy pricing is not a new concept and has been used in various guises for several decades.

The first discussion of variable energy pricing began to emerge in the early 1950’s, with Houthakker calling for the introduction of a so-called “time-of-day tariff” in response to emerging difficulties in meeting peak loads (Houthakker, 1951). However, as is the case with DR, the concept of variable energy pricing gained true momentum during the early 1970’s as a result of mounting concerns over oil supply and the resulting impacts on security and cost of supply. The intended outcome was simple - vary the times of day that consumers would use energy, by altering the price of energy during certain periods.

Early examples of the application of variable energy pricing include the UK’s Radio Teleswitch system, which allowed electric storage heaters to be controlled remotely through a signal which was embedded in radio broadcast signals, thereby allowing operators to spread/shift considerable load, whilst granting consumers (many of whom had little or no alternative to electric heating) access to reduced tariffs (Ofgem, 2013; Radio Teleswitch Services, 2016). Another high profile early example from the UK is Economy 7, a two-tiered differential tariff which was introduced in 1978, at a time when electric storage heaters were gaining in popularity (The Electricity Council, 1982). Economy 7 was also designed to shift domestic heating loads from the daytime to the night, thereby reducing the daily variation in demand. This is achieved by creating an off-peak pricing period seven hours in length during which storage heaters (or other appliances) could be switched on, allowing them to release their heat into the home over the course of the following day. These examples of variable pricing are still available today, though less popular given the decline in the use of electric storage heaters.

During the same period, variable energy pricing was being trialled in America, including most notably the Wisconsin Residential Time-of-Use Electricity Pricing Experiment. This experiment involved around six hundred domestic consumers, who were exposed to energy pricing strategies featuring a ‘peak’ and an ‘off-peak’ period. A total of ten variations were used, which varied according to the ratio between peak and off-peak prices and the duration of the peak period. (Caves & Christensen, 1980) provide an overview of the experiment in their 1980 paper on the quantification of the resulting changes in demand (a subject that is discussed in more detail later in this section).

By the early 1990’s, enough pilot and trial projects had been conducted to enable (Hill, 1991) and others to make meaningful comparisons of the success of each, and to identify trends. Hill concluded that Time of Use (ToU) energy pricing was a cost-effective approach to the shifting of loads from peak to off-peak periods, whilst also noting that the cost and difficulty associated with the associated metering was a significant barrier.

In more recent years the application and complexity of variable energy pricing strategies has increased significantly. As discussed in the previous chapter, the understanding of the social and behavioural aspects of variable pricing - and of DR in general - has also increased, thereby prompting researchers and policy makers to consider how best to apply variable energy pricing.

4.1.2 Forms of variable pricing

There are a number of different forms of variable energy pricing, each of which differs in the nature and desired extent of the resulting response. These range from simple peak demand reduction to more extensive load management and the promotion of near-instantaneous response. In order to achieve these aims, each approach varies in the following three main ways:

1. The timescale over which the price variation occurs.
2. The advance notice given to consumers regarding price variations.
3. The basis or ‘driver’ of price variation.

The first of these factors concerns the length of time each pricing level is applied, and therefore the frequency with which the price of energy changes. This ranges from seasonal to hourly or even sub-hourly timesteps. The advance notice given to consumers regarding upcoming price variations and levels is intrinsically linked to the variation timescale, with more frequent variations likely (but not guaranteed) to result in shorter notice periods. Lastly, the basis for price variation can also differ between approaches. This relates primarily to the desired outcomes of each approach. If for example the aim is to reduce peak demand then the basis for price variation will relate to peak periods. Alternatively if the aim is to maximise the utilisation of existing generation capacity, then price variations will be aimed at reflecting capacity levels.

Darby differentiates between such desired outcomes by categorising DR initiatives as being either ‘static’ or ‘dynamic’ (S. J. Darby, 2013). Static approaches to variable pricing can be defined as those which are able to achieve their intended response by using price variations which remain fixed for long periods of time which can be identified far in advance. Strategies which take this approach are typically aimed at reducing peak demand, which occurs at regular and predictable intervals. When more short-term response is sought, a higher resolution of price variation is required, whereby pricing can be changed frequently, irregularly and with comparatively short notice. This is referred to as dynamic pricing or Real Time Pricing (RTP), and is discussed in more detail below.

A more detailed overview of the various forms of variable pricing is provided by (Doostizadeh & Ghasemi, 2012) who categorise the main types of time-based energy pricing into the following:

- Seasonal flat pricing.
- Peak day rebates.
- Critical Peak Pricing (CPP).
- Time of Use (ToU) pricing.
- Real Time Pricing (RTP).

As discussed above, each of these approaches varies in timescale over which price variation occurs, the frequency with which price changes, and the basis for price variation. However, whilst variable pricing approaches can be categorised in this way, there remains significant scope for similar approaches within each category to vary significantly.

Seasonal flat pricing refers to an approach which sees the price of energy fixed within each season. Of all the variable pricing strategies, this involves the longest variation timescale and the greatest amount of advance notice to consumers. The use of such a long time period means that short-term variations in wholesale market conditions cannot be passed on to consumers. As such, it will not be subject to further study in this project.

Peak day rebates are also not included, as this approach to DR is incentive-based rather than price-based. This approach works by awarding rebates on an ex-post basis for avoided consumption during peak times, typically days/periods when the system is under particular stress. One central criticism of Peak Day Rebates stems from the need for a reliable baseline consumption against which to measure actual consumption and then pay rebates. When used on an opt-in basis, the use of historical data to provide this baseline leads to a higher rate of adoption from consumers who have reduced their demand relative to the previous year (and who, as a result, would be in line for the greatest rebate payments). This could lead to growing households being punished and shrinking households benefiting, both disproportionately.

The same also applies to interruptible demand programs, which involve consumers agreeing to allow the system operator or utility to curtail demand, usually in return for a reduction in (flat or ToU) energy rate, or bill credit. System operators and utilities are more likely to favour interruptible demand programs as they do not rely on consumers taking action in order to respond, given that consumer action is much less reliable due to the fact that response is optional. However, as well as being less socially desirable, this has economic disadvantages - the cost of reducing the demand of a small number of consumers by a large percentage is likely to be larger than the cost of curtailing a large amount of consumers by a small amount. This led Borenstein to describe interruptible demand programs as “very imperfect substitutes for CPP or RTP.” (Borenstein, Jaske, & Rosenfeld, 2002). Most importantly however, (Aalami, Moghaddam, & Yousefi, 2010) note that interruptible demand programs are typically only applied to consumers of 200kW or more.

The remainder of this section will therefore focus on the three main forms of variable energy pricing: CPP, ToU and RTP. These three approaches make up the vast majority of past research into variable pricing, and are considered to be most appropriate for domestic applications (Albadi & El-Saadany, 2007; Faria & Vale, 2011; Newsham & Bowker, 2010).

4.1.3 Time of Use pricing

ToU pricing is used to describe any variable energy pricing structure which sees the price of energy vary across two or more time periods of fixed duration. The price during each of these fixed periods is set in advance, either hourly, weekly, monthly, seasonally or annually, but is typically adjusted a few times a year (Borenstein et al., 2002). The duration of the price periods themselves can also range from a few hours to an entire season in length. Some forms of ToU pricing can be defined as being static in nature, if the variation timescale and advance notice period are similarly long. As the advance notice and time period decreases, so does the potential exposure of consumers to risk.

ToU pricing is similar to CPP in that it can also be used to reduce peak demand. However, through the use of various different pricing points, ToU can also be used to shift demand from one period to another. This also means that it is more capable of reflecting the wholesale cost of electricity, or the cost of producing it at different times of day/year etc. For this reason, ToU can be seen to encourage a broader range of DR, which becomes more dynamic in nature as the timescale decreases. It should be noted that the nature of consumer response to ToU can also vary significantly as the timescale changes i.e. the change in consumption patterns and habits which results from seasonal variation in energy pricing is likely to differ fundamentally from that which results from multiple variations within a single day.

The limitations associated with ToU include the constraints placed upon its ability to reflect changes in system stresses and wholesale energy costs which result from the fact that pricing periods are of a fixed duration. For this reason, ToU is regarded by some as being an inferior substitute for the more complex RTP approach, which is discussed in more detail below. In his study of RTP, (Borenstein, 2005) includes an element of ToU analysis to provide some comparison, but finds it to result in less than 20% of the efficiencies achieved by RTP.

Since the emergence of early examples such as the aforementioned Economy 7 tariff, there have been a great number of applications of ToU pricing. It can therefore be seen as a relatively well known and understood approach to variable energy pricing in comparison to others. A comprehensive review of ToU pricing and its implementation is provided by (Faruqui & George, 2002).

Recent notable examples include the California state-wide pricing pilot (2003-4), the results of which are presented by (Owen & Ward, 2010). This pilot study saw the introduction of three pricing levels: a peak price which was 70% higher than the normal rate, and a low rate which was half the peak rate. Over the two year scheme, no overall reduction in domestic consumption was observed, with reductions during peak pricing hours being cancelled out by increases in consumption during reduced pricing hours. A similar result was obtained by Torriti, who assessed the results of a ToU scheme in Trentino, Italy (Torriti, 2012). While overall consumption was found to increase by over 13%, household energy bills were found to decrease by over 2% during the same period. This is indicative of the fact that ToU, unlike CPP, is not focussed exclusively on the reduction of peak demand, and instead is concerned with altering the timing of consumption. The inclusion of a pricing level which is lower than the standard rate has also been found to result in consumers increasing their consumption during such periods, thereby cancelling out (and even reversing) the effect of increased pricing levels on overall consumption. This is commonly referred to as the rebound effect (Gillingham et al., 2009).

4.1.4 Critical Peak Pricing

CPP involves the introduction of a peak pricing rate - usually several times greater than a standard (or ToU) rate - which is triggered during times of system stress i.e. times of high network-wide demand. During these periods, which are typically one to six hours in length, the application of a ‘peak’ price encourages consumers to reduce their consumption. This can be done either by load shifting or load curtailment.

Borenstein et al. suggest that most CPP programs are applied to an existing ToU rate structure, and argues that CPP represents a significant improvement upon ToU due to the fact that emphasis is placed on network stress and not consumer demand (Borenstein et al., 2002).

CPP is seen as the logical first step towards variable pricing that is facilitated by the availability of smart metering. Due to the emphasis placed on avoiding/alleviating network stress, it is primarily applied with the aim of reducing peak demand and has been found to compare favourably with other more complex variable pricing strategies when it comes to achieving peak demand reductions (Newsham & Bowker, 2010).

Typically, a limit is applied to the number of peak periods that can be triggered each year. This is seen as one of the main economic weaknesses of CPP, with the other being the fact that pricing levels are pre-set, which makes CPP less able to respond to energy market conditions. These weaknesses are seen to reflect the interests and concerns of energy providers and network operators rather than those of consumer, and could actually serve to make CPP more socially desirable from the consumer perspective (Borenstein et al., 2002).

A number of residential trials of CPP have taken place in recent years, most notably in California (Herter, McAuliffe, & Rosenfeld, 2007; Wolak, 2007). These two studies obtained very similar results, with reported decreases in consumption during peak pricing periods of 13% and 12%. Interestingly, the study presented by (Herter et al., 2007) also included the introduction of “automated end-use control technologies” to help facilitate DR. The results led the authors to argue that the domestic sector is capable of contributing significantly to system stability and reliability through the application of CPP. A similar conclusion is also reached by (Newsham & Bowker, 2010), who argue that the combination of CPP with “enabling technology” is the most effective approach towards promoting domestic DR.

Herter also provides a more in-depth analysis of the impact of the introduction of CPP from a consumer point of view (Herter, 2007). She finds that households who consume the most energy are likely to respond the most to peak pricing periods, but see a smaller resulting reduction in energy bills (1.7%) than those who consume less energy overall (4%). It should also be noted that the introduction of CPP caused household energy bills to both increase and decrease. The results are also analysed relative to household income levels, though little variation was found to exist when it comes to consumer satisfaction, load reduction or bill reduction. This is a particularly significant result, as it suggests that the application of CPP will not result in particular socio-economic consumer groups being disadvantaged. The importance of the distribution of the rewards from variable pricing is discussed in more detail in section 4.2.

4.1.5 Real Time Pricing

Real Time Pricing (RTP) has the shortest variation timescale and potentially the shortest advance notice period of all the forms of variable pricing, and as such is intended to result in demand which is truly responsive. RTP resembles some forms of ToU pricing in many ways, but often features shorter timestep durations, which are not of fixed duration (Borenstein et al., 2002).

Under RTP, prices typically change hourly in order to reflect variations in the price driver - normally wholesale market prices or the marginal cost of generation (Allcott, 2011; Ulbig & Andersson, 2010). Prices are announced on either a day-ahead or an hour-ahead basis. This pricing strategy exposes the consumer to a greater degree of risk (through price variation) than the aforementioned strategies, but is capable of creating a highly responsive demand profile.

True RTP prices can only be calculated on an ex post basis, but this is seen as being undesirable due to the fact that consumers are not aware of the actual price at the time of consumption. Ex ante forms of RTP vary according to the amount of advance notice given. These range from day-ahead to near real-time, and involve forecasting to varying degrees. The forecasting of grid-connected RTP is subject to influence by a range of highly complex phenomena, including wider market conditions (including hourly spot market conditions), marginal cost calculations etc. (Borenstein et al., 2002).

In order to shield consumers from (undesirable) exposure to high prices, some RTP programs charge a flat rate for a baseline of consumption, and apply RTP to anything over and above this level. However, this customer baseline load (CBL) approach has been found to be flawed, as it can be seen as either a tax or a subsidy, depending on whether the baseline price was above or below the market price. Such an approach also can also lead to a significant lobbying and influence problem (Borenstein et al., 2002). Another “risk-hedging device” involves consumers setting their own baseline, which is purchased at a price that reflects the predicted real-time price. This allows consumers to protect themselves from as much price risk as they want.

RTP is an attractive prospect from a theoretical economic perspective as it provides supplier benefits and offers consumer incentives. However, the theoretical evaluation does not convey the extent of these gains, which have been found to vary significantly in real-world applications (Borenstein, 2005). As discussed before, the ability of consumers to respond to variable pricing has a profound effect on their resulting benefit. This is noted by Lujano-Rojas et al., who demonstrate the potential for consumer benefits and high levels of DR that are possible when consumer desire to engage with RTP is coupled successfully with enabling technology (Lujano-Rojas, Monteiro, Dufo-López, & Bernal-Agustín, 2012).

The ability of RTP to respond quickly and accurately to changes in wholesale energy costs brings with it significant complexity when it comes to metering, billing, and most importantly the need for consumer engagement. For this reason, it is regarded as the most complex of the variable energy pricing strategies, and therefore most likely to meet resistance from those who oppose complexity (not to mention the exposure of consumers to risk) in energy pricing. Darby claims that the case for real-time pricing (RTP) in the UK has “yet to be made”, but also notes that increased deployment of distributed generation could facilitate its wider deployment in the future (S. Darby, 2006).

RTP is regarded by many as being the best form of variable energy pricing, due to its flexibility, and its resulting ability to reflect the driver for price variation (typically wholesale energy costs) more accurately than others. There is also evidence to suggest that the introduction of RTP can benefit all consumers, even if only a small proportion are actually subject to RTP pricing. Holland and Mansur found that when RTP is implemented, all consumers - even those who remain on flat rate pricing - benefit from its introduction (Holland & Mansur, 2006). This is due to the fact that the benefits of avoided additional generation capacity investments are shared amongst all consumers (with RTP participants still able to achieve further bill reductions through direct engagement with RTP). This suggests that not all consumers must participate in RTP in order for widespread benefits to result. Borenstein goes further still, in arguing that as the proportion of consumers under RTP increases, its effectiveness decreases (Borenstein, 2005). Borenstein also argues that the introduction of RTP can yield significant results even when demand elasticity (a topic which is discussed later in this chapter) is low. This view is shared by Sioshansi and Short, who found RTP to be capable of increasing the utilisation of wind generation, even with low elasticities (Sioshansi & Short, 2009). This is seen as a key benefit of RTP, and is one which is not replicated by other variable pricing strategies such as those discussed previously. For that reason, Borenstein concludes that ToU is “likely to capture a very small share of the efficiency gains that RTP offers” (Borenstein, 2005).

However, Borenstein also highlights some of the potential drawbacks associated with this approach, citing the difficulties relating to the equitable distribution of the benefits of RTP’s use which can arise if not all consumers are on RTP tariffs. This largely stems from the fact that those with “attractive” load profiles would be more likely to sign up, given that they would be more likely to save money (Borenstein et al., 2002). This view is echoed by Salies, who deems RTP to be incompatible with widespread use (Salies, 2013). This again highlights the importance of the equitable distribution of the benefits of variable pricing, and the likelihood of resistance from significant proportions of society.

4.2 The Viability of Variable Domestic Energy Pricing

The viability of variable energy pricing is dependent on a number of key factors. Firstly, both consumers and suppliers must have the required infrastructure and equipment in place in order for it to be implemented successfully. Typically, this involves the use of high resolution energy metering i.e. smart metering on the consumer side, and the reporting and billing infrastructure on the supplier side. Consumers must also have all the information required to enable them to a) make an informed choice about whether or not to adopt variable pricing tariffs in the first place, b) understand the pricing tariff and how it is applied and c) fully understand the risk and reward implications associated with variable pricing. Each of these steps is considered crucial, and represents a significant challenge to the widespread implementation of variable domestic energy pricing.

Due to the scale of these challenges, and the vast differences compared to conventional flat rate energy pricing, it is likely that the introduction of variable pricing will continue slowly and carefully. As noted by Borenstein et al., reliance on price-responsive demand is unlikely to emerge for some time. However, the same authors also predict that with increased forecast reliability and the resulting quantification of price-response, variable pricing will be able to play an increasingly important role in the future (Borenstein et al., 2002).

4.2.1 Consumer attitudes

Much of the research in variable pricing which has been conducted to date has focussed primarily on its technical and economic viability (S. J. Darby & McKenna, 2012; Marzband, Sumper, Ruiz-Álvarez, Domínguez-García, & Tomoiagă, 2013). However, the application of variable pricing is ultimately pointless if it does not have the support of the consumers adopting it. The need for further research into consumer attitudes towards variable pricing is acknowledged in a report on smart tariffs and DR prepared by Sustainability First, which presents the findings of UK market regulator Ofgem's "Consumer First" initiative (Owen & Ward, 2010). The importance of social viability is also echoed throughout academic literature (S. J. Darby & McKenna, 2012; McKenna, Ghosh, & Thomson, 2011).

The findings from past attempts to gauge consumer attitudes towards variable pricing can vary significantly, from largely resistant to mainly receptive. Recent consumer research has indicated a great deal of scepticism towards variable pricing amongst domestic consumers (Downing & Icaro Consulting, 2009; Opinion Leader, 2009). Generally speaking, this is found to stem from the following key areas:

- A lack of understanding of energy pricing in general.
- Mistrust of energy retailers.
- Concerns regarding fairness and the distribution of benefits.

- The perceived level of engagement required.

As discussed in the previous chapter, understanding of the social and behavioural factors which influence domestic energy consumption has increased significantly since DR was first discussed. More recently, this has expanded to include the consideration of how consumers view DR and variable pricing. This growing body of research has seen the emergence of a number of key areas relating to consumer attitudes and social viability. Chief amongst these is the need for understanding on the part of consumers. As stressed by Darby and McKenna and others, this is arguably best achieved by ensuring the simplicity of variable pricing tariffs (S. J. Darby & McKenna, 2012). The need for simplicity and clarity of explanation was also identified by UK electricity market regulator Ofgem, as part of their “Consumer First” consumer research (Opinion Leader, 2009). This research identified an existing lack of understanding even when it comes to existing (conventional) energy pricing tariffs. This indicates the scale of the shift in knowledge and understanding that is required before more complex variable pricing tariffs can be introduced successfully.

The Consumer First findings also indicate that consumers are likely to be more receptive towards variable pricing which rewards energy efficient consumers rather than punishing inefficiency and high consumption. This is linked to concerns surrounding the perceived fairness of variable pricing, particularly when it comes to large families and vulnerable groups i.e. those whose capacity to respond to price variations is limited, and those likely to be negatively affected by variable pricing. This view is supported by another study of consumer attitudes conducted by Icaro consulting on behalf of the UK Green Building Council and the Zero Carbon Hub (Downing & Icaro Consulting, 2009).

Another common concern relating to variable pricing is the effort required to implement DR. Once again, this points to the need for consumer education, and alludes to the perception of sustainable consumption as requiring some form of 'sacrifice', as discussed by Kaplan (Kaplan, 2000).

As stated above, there is some research which appears to suggest that consumers are in fact receptive to variable pricing. An example of this is provided David et al., whose results indicate that consumers were generally willing to adopt a variable pricing system. Around half of respondents reported willingness to do so even if the resulting financial savings were less than 10%, with 80% willing to do so for savings of around 20% (David, Nutt, Chang, & Lee, 1986). This contrast in findings not only highlights the importance of the sampling methods used in consumer surveys (David et al.'s respondents consisted primarily of academic students and staff) but also suggests that there is much still to be learned when it comes to consumer attitudes.

The way in which consumers benefit (or otherwise) from the introduction of variable pricing is another crucial factor when it comes to social viability. Much of the existing consumer research indicates that the distribution of the benefits and penalties associated with variable pricing is a key consumer concern (S. Darby, 2006; Opinion Leader, 2009). However, whilst this is an understandably important concern, there is little in the way of evidence which suggests that this concern is translated into reality. A particularly interesting study into this area was conducted by Herter (Herter, 2007), who conducted an examination of the variation in the impact of CPP on domestic consumers, according to consumption levels and household income. The results indicated that both load and bill changes were equal across all household income levels, as were satisfaction levels. Similarly, there is also concern that despite being touted as beneficial to both utilities and consumers, the consumer benefits are not proportionate to the benefits enjoyed by the utilities

(Kirschen, Strbac, Cumperayot, & de Paiva Mendes, 2000). This is likely to stem from the mistrust that exists among consumers towards energy retailers (Devine-wright & Wiersma, 2013; Opinion Leader, 2009; Strong & Which?, 2014) However, this remains difficult to quantify.

There are numerous examples of reduced energy bills resulting from participation in variable energy pricing trials, which suggests that there is indeed a financial benefit to be had for consumers (Dupont, De Jonghe, Kessels, & Belmans, 2011; Lujano-Rojas et al., 2012). However, it should be noted that exposing consumers to greater levels of financial risk that require responsive behaviour can and does lead to price/bill increases (S. Darby, 2006). There is also evidence that the benefits of variable pricing to consumers can go beyond financial reward, with Aubin et al. (Aubin, Fougère, Husson, & Ivaldi, 1995) asserting that the introduction of variable pricing improved the welfare of the majority of participants. Similarly, Dupont et al. argue that dynamic price-based DR “brings benefits to participants and society as a whole” (Dupont et al., 2011).This is an aspect of variable energy pricing which appears to be relatively poorly understood (due in part to the difficulties in quantifying the benefits) and is seldom communicated to potential consumers.

4.2.2 Engagement with variable pricing

When it comes to the way in which consumers engage with variable pricing, once again the issue of complexity and consumer understanding is paramount. The extent to which any consumer is willing and able to engage with variable pricing is dictated by their level of understanding of the pricing structure in place, and their ability to respond to price variations.

Given the importance of consumer understanding, it follows that the temporal resolution of pricing data should therefore only be as high as the consumer’s ability to react to it. For instance, if a household doesn’t have a sufficient level of control to automatically shift or curtail loads on an hourly basis, then there is little use in supplying hourly data. Furthermore, superfluous detail is likely to confuse and disengage household consumers. These issues also highlight the need for a cohesive approach towards variable pricing which extends to include considerations of how consumers enact DR.

Due largely to the potential for unresponsive consumers to see their bills increase, participation in trial schemes has to date been almost exclusively voluntary (Borenstein et al., 2002; He & Kua, 2013; Herter & Wayland, 2010; Keane & Goett, 1988; Kim & Shcherbakova, 2011; Lujano-Rojas et al., 2012). It is considered likely that consumers who volunteer to participate in voluntary schemes will exhibit greater flexibility than those who did not, as the act of volunteering suggests an interest in DR or a desire to reap the rewards. Therefore if participation was mandatory, consumers who would have otherwise chosen not to engage in variable pricing studies would be effectively forced to do so. Given the moral and financial difficulties associated with such circumstances, little is known as to how such consumers (who are likely to represent the majority given the findings of the aforementioned consumer research) would engage with variable pricing.

The nature and sustainability of consumer response to variable pricing is also subject to much debate, with significant differences identified between initial and short-term response, and longer term response. Over the longer term, consumers are considered more likely to respond to price increases by purchasing more energy efficient appliances (Spees & Lave, 2007). However, for variable energy pricing (and particularly in the case of near real-time price variation) it is the short-term response of consumers which is of key interest.

Another key aspect which is pivotal to the success of variable pricing schemes is the distribution and extent of the resulting financial rewards/costs (Bradley, Leach, &

Torriti, 2013). Whilst utilities recover the cost of implementing such schemes through cost recovery and lost revenue mechanisms, the extent to which consumers are rewarded for their engagement is often found to be a barrier to the success of such schemes (Torriti & Leach, 2012). As financial incentivisation is central to the success of variable pricing schemes, this is an area of significant importance. Torriti and Leach also stress the need for the distribution of the financial rewards/penalties to be carefully considered, and propose a mechanism for doing so which is based on cumulative benchmarks.

4.2.3 Response automation

The ability of consumers to respond to price variations has until recently been a severely limiting factor on the viability of variable domestic energy pricing (Mohsenian-Rad & Leon-Garcia, 2010). However, the emergence of increasingly sophisticated and capable automation technology means that the onus can largely be shifted from the consumer to such technology.

As discussed in the previous chapter, the means and extent of this shift remains the subject of some debate. However, there appears to be a widely held consensus that automation technology will play an increasingly significant role in DR in general in the future (Borenstein et al., 2002; Buryk, Mead, Mourato, & Torriti, 2015; Ericson, 2009; Faruqui & George, 2005; Newsham & Bowker, 2010; Saffre & Gedge, 2010; Spees & Lave, 2007). As a result, the introduction of variable energy pricing can therefore be seen to be reliant on the effective deployment of automation technology.

The importance of automation technology in reducing the required level of consumer engagement is well summarised by Aubin et al. who identified that the ability of consumers to respond to variable pricing is a major barrier to its widespread implementation, as it prevents the benefits and drawbacks from being shared equally among participants (Aubin et al., 1995). The same authors also argue that without sophisticated energy management in place, the introduction of variable pricing is likely to require too much effort from the consumer - a view that is echoed by (Spees & Lave, 2007).

Often referred to as ‘enabling technology’ or ‘response automation’, this umbrella term refers to the following aspects of DR:

- Direct load control: the ability to control specific loads/appliances instantaneously, in response to pricing signals (Ericson, 2009; Samadi, Mohsenian-Rad, Schober, Wong, & Jatskevich, 2010).
- Load scheduling: technology which can schedule certain loads/appliances for certain times of day, or when energy prices reach certain pre-defined levels (Dupont, Tant, & Belmans, 2012).
- Feedback and communication: a rapidly developing area. This relates to information which is supplied to consumers to inform them of their current, past and predicted consumption levels. This can be supplied instantaneously (via dedicated units and displays) or indirectly through billing, and can be incorporated into targeted DR initiatives.
- Smart metering: next generation metering equipment intended to provide accurate consumption information in real-time and at high resolution, resulting in more accurate billing and real-time feedback/information for consumers.

The primary benefits to the consumer from using automation technology are twofold. Firstly, it reduces the need for consumer to engage frequently with potentially rapidly changing pricing signals, thereby reducing the effort required to adapt to variable pricing. Secondly, it allows consumers to maximise the benefits of engaging with variable energy pricing, such as those discussed above (Faruqui &

George, 2005; Hammerstrom & Ambrosio, 2007; Lujano-Rojas et al., 2012). The use of technology has also been found to be beneficial to energy suppliers, particularly in the case of direct load control (Samadi et al., 2010).

The potential contribution of automation technology in facilitating DR in a way that is beneficial for consumers is also reflected in the apparent willingness of consumers to adopt it (Clastres, 2011). However, this issue is more complex than it may appear, especially when it comes to consumers sacrificing control of their domestic energy consumption. Again, the results of Ofgem's Consumer First research provide a useful insight into consumer attitudes on the matter (Opinion Leader, 2009). The following excerpt raises a lot of interesting issues:

"Many suggested they would need to make substantial behaviour changes, such as having appliances on a timer, or changing the time of day when they do their cooking or washing, to make cost savings. Most Panel members felt these changes are too much effort." (Opinion Leader, 2009)

This shows a level of awareness of automation technology, and that an association is made between variable pricing and its use. However, it is also suggests that the use of technology may not be seen to reduce the perceived level of engagement required. This further underlines the importance of consumer knowledge and understanding, and also suggests that the capabilities of technology (particularly when it comes to load control and load shifting/scheduling as mentioned above) need to be effectively communicated to consumers. It is thought that doing so would likely reduce the perceived effort and level of engagement required on the part of consumers, which in turn could improve the social viability and acceptance of variable pricing.

The capability and development of automated response technology has risen dramatically within the last two decades. As a result there are an increasing number of examples of its deployment, such as Figure 4-1, which shows the combination of enabling technology with financially-motivated DR in the form of a commercially available product/service which is currently on sale in the United States.

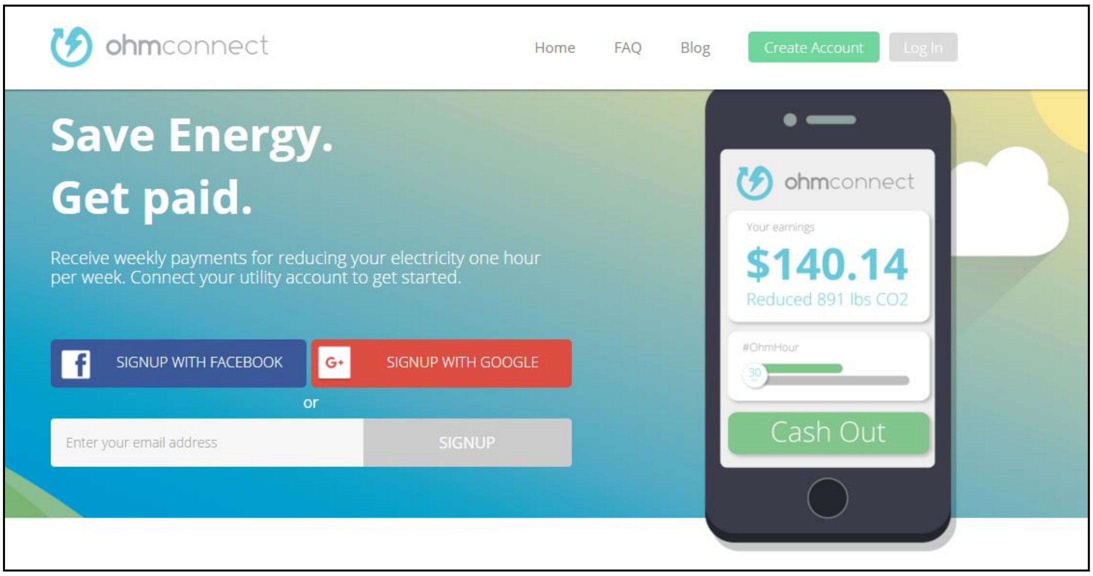


Figure 4-1 - An example of the combination of enabling technology and financially motivated DR in a commercial context (ohmconnect, 2015)**.**

Arguably the simplest form of automation technology is direct load control. This involves the disconnection of certain loads from the network in order to minimise peak consumption. The fact that this involves handing control over elements of domestic consumption over to external parties raises a number of issues when it comes to social viability (S. J. Darby & McKenna, 2012). As such, it is typically limited to low-impact loads such as water heaters (Ericson, 2009).

Load scheduling can be seen as a step up in terms of sophistication, in that it facilitates the shifting of loads rather than the curtailment. (Dupont et al., 2012) present a load scheduling algorithm which is used to schedule the loads associated with white goods. This takes into account both pricing signals and pre-programmable consumer preferences. The importance of consumer override is also identified by (Newsham & Bowker, 2010). While allowing for consumer override has obvious social viability benefits, the effectiveness of its inclusion can limit the effectiveness in the eyes of the network operator.

One notable example of the application of smart technology which has the specific aim of facilitating the integration of renewable energy into microgrids is the Ecogrid EU project. This large scale application sees over 2000 domestic consumers equipped with automated load control devices (and smart metering), with the aim of utilising reactive loads which can be controlled either remotely or by consumers (Ding et al., 2012).

The various elements of all automation technologies can also be usefully combined, as demonstrated by Di Giorgio and Pimpinella's "Smart Home Controller" (Di Giorgio & Pimpinella, 2012). This represents the peak of load control sophistication, in that it distinguishes between plannable, controllable, monitorable and detectable loads, and is designed to maximise the benefit to both the consumer and the network operator. A similar study was conducted by Lujano-Rojas et al., who demonstrate the ability of an optimal load management strategy to maximise the ability of domestic consumers to respond to variable pricing (Lujano-Rojas et al., 2012). This study was also verified by application in Zaragoza, Spain, with positive results, and represents a benchmark for the contribution of enabling technology when used in combination.

4.3 Domestic Demand Elasticity

4.3.1 The price elasticity of domestic energy demand

The relationship between the price of energy and the level of demand for it is fundamental to variable energy pricing, as it is with any product or service. There are two ways in which consumers can respond to price variation:

1. Reduce or increase their consumption.
2. Shift/postpone their consumption to lower price periods.

In the field of economics, the responsiveness of the demand for a product or service to changes in its price is known as consumer price elasticity of demand (CPED. It is also referred to as self-price elasticity). This is illustrated in Figure 4-2, which shows a typical demand curve and illustrates the reduction in the quantity demanded ($q_0 \rightarrow q_1$) which results from an increase in price ($p_0 \rightarrow p_1$).

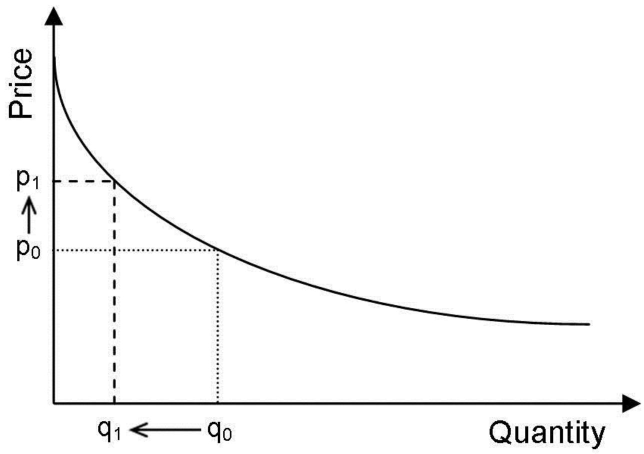


Figure 4-2 - Graph showing a typical relationship between price and demand quantity.

In practice, this curve is often very difficult to accurately define, and is therefore commonly linearized around known points, with the relative slope between these points then defined as the price elasticity of demand. The price elasticity of demand (ε) as shown in Figure 4-2 can be expressed using Equation 1:

$$\varepsilon = \frac{\%\Delta q}{\%\Delta p} \tag{1}$$

where:

ε	=	Price elasticity of demand
$\%\Delta q$	=	Percentage change in quantity consumed
$\%\Delta p$	=	Percentage change in price

The elasticity of demand (as covered above) relates to the curtailment and growth of loads relative to changes in the cost of energy. The temporal shifting of loads on the other hand does not result in a change in the overall demand associated with a given time period, and so requires a different form of elasticity, known as the elasticity of substitution. In conventional economic theory, this refers to the change in demand for one product or service which results from the change in price of another e.g. the change in demand for pens which results from the increase in the price of pencils. In the context of DR however, energy demand at one time period is used as a substitute for energy demand at another, so although the actual product is the same, they can be seen as different as they differ in price and timing.

There are two main elasticity of substitution models found in the literature (Biviji, Wang, Ostrowski, & Wang, 2012; Braithwait, 2000; Ton, Biviji, Nagypal, & Wang, 2013). The first and most commonly used is the Constant Elasticity of Substitution (CES), which assumes elasticity of substitution values remain constant regardless of demand level. The more complex Generalised Leontief (GL) model allows for the variation of elasticity as demand levels change, and despite being more flexible, is often neglected in favour of the less computationally complex CES model (Caves & Christensen, 1980). It is for this reason that the CES model was also deemed most appropriate for this project. The values used are discussed further in section 6.2.7.

CES can be defined as the negative of the percentage change in the ratio of electricity consumption in two different time periods that occurs in response to a given percentage change in the relative price between the two periods (King & Chatterjee, 2003). Relationships which have an elasticity value furthest from zero are the most elastic. This is expressed below in Equation 2:

$$\sigma = -\frac{\%\Delta(\frac{Q_p}{Q_o})}{\%\Delta(\frac{P_p}{P_o})} \tag{2}$$

where:

σ	=	Elasticity of substitution
Q_p, Q_o	=	Peak and off-peak demand quantities
P_p,P_o	=	Peak and off-peak prices

4.3.2 Elasticity as a proxy for consumer behaviour

CPED values are central to the study of consumer response to variable energy pricing, and are used to quantify the responsiveness of consumers to price variation. However there remains some doubt as to whether elasticity values alone can accurately represent consumer response to energy price variation.

A consumer's demand elasticity is a function of a combination of complex and inter-related factors. As discussed in the previous chapter, these include factors such as income, habits, attitudes and social norms. As noted by (David & Li, 1991) rationality also has a role to play in governing response decision taken by consumers. This relates to the fact that not all consumers can be expected to act in a rational way, as they are influenced by attitudes, habits and other social norms which result in sub-optimal decisions being made (at least from a strictly financial perspective). This is reviewed in more detail by Gillingham et al., who claim that approaches which assume that consumers exhibit imperfect rationality "have intuitive psychological appeal as well as an empirical basis from behavioural economic and psychological studies." (Gillingham et al., 2009).

Nevertheless, the uncertainty and subjectivity associated with many of the behavioural and social factors which contribute towards consumer elasticity mean that elasticity is still considered to be an appropriate proxy for consumer behaviour. This is reflected in the literature, with numerous examples of elasticity values being used to characterise and represent consumer response to price variations e.g. (Conejo, Morales, & Baringo, 2010; Faria & Vale, 2011; Kirschen et al., 2000).

4.3.3 Quantifying domestic elasticity

As previously stated, the demand curves associated with most commodities are often very difficult to define accurately. This is particularly true when it comes to domestic energy demand, given the range of contributing socio-economic and behavioural factors. However, given its central importance to the study of consumption behaviour and variable energy pricing, it has nevertheless been the subject of much research in recent years.

One crucial distinction that must be made when attempting to quantify elasticity is the timeframe over which changes in demand are assessed. This is most commonly categorised into long-term and short-term, with the latter being defined as anything less than a year, and the former anything over a year (Bernstein & Griffin, 2006; Lijesen, 2007). The importance of this distinction stems from the differences in how elasticity is exhibited across each timescale. Short term elasticity refers more directly to changes in consumption, whereas long term elasticity can be extended to include improvements in efficiency, which results in a change in demand levels. In the domestic context in particular, this can be influenced by the purchasing of efficient appliances.

One of the most comprehensive reviews of research into domestic elasticity was conducted by Lijesen, who summarised past research in an attempt to quantify elasticity values in both industrial and domestic applications (Lijesen, 2007). The research surveyed by Lijesen spans a range of different elasticity models and timescales, and encompasses research conducted from as far back as 1955. As a result, the elasticity values also vary significantly. The findings of Lijesen's review show long term elasticities to be consistently higher than short term elasticities, as they allow more scope for adapting energy consuming stock and alterations to energy efficiency which are not feasible or economical in the short run. This result is echoed in much of the literature (Bohi & Zimmerman, 1984; Dahl & Sterner, 1991; Taylor, 1975).

Lijesen also reviews elasticity estimates from ToU pricing applications. A distinction is made between 'peak' and 'off-peak' elasticity - which accounts the difference in elasticity which occurs under different pricing levels under ToU pricing. This incorporates more specifically the impact of both demand reduction and load shifting i.e. both self-price elasticity and the elasticity of substitution, and can therefore be seen as being more relevant to the field of variable energy pricing. The resulting elasticities from such applications are quite small however, leading Faruqui and George to conclude that "the demand for electricity by time of use is inelastic in the short run" (Faruqui & George, 2002).

The relationship between own-price elasticity and elasticity of substitution was also investigated by Caves and Christensen, who found that an elasticity of substitution of 0.17 was consistent with an own-price elasticity of -0.3 (Caves & Christensen, 1980). This provides some indication of the link between the two values, by suggesting that a given level of own-price elasticity may correspond to another level of elasticity of substitution.

Further research into the differences in elasticity between peak and off-peak pricing periods was conducted by (Filippini, 1995), who based an estimation of elasticity values on a sample of 220 households across 19 Swiss cities, all of whom had access to time differential energy pricing. Filippini's result suggest that demand was significantly more elastic than previous research (such as that reviewed by Lijesen) had indicated, with peak price elasticity ranging from -1.25 to -1.41 and off-peak elasticity even greater at -2.3 to -2.57. Elasticity of substitution values ranged from 2.56 to 2.98. These results suggest a level of elasticity which is far beyond most estimates. Interestingly, Lijesen attributes this to misspecification.

As part of their analysis of the potential of domestic ToU pricing, Tracey and Wallach (Tracey & Wallach, 2003) also outline the various estimates of elasticity of substitution values from various previous experiments into variable energy pricing. The results of this are shown in Table 4-1, and show voluntary schemes to have higher elasticity values than mandatory ones - a view which is supported by (Hill, 1991). Tracey and Wallach also note that customers with electric heating were found to have far higher elasticities than those without, with the Midwest Power System experiment resulting in elasticity values of 0.15 and 0.39 respectively. This alludes to the high degree of flexibility that can be attributed to electric water heating loads.

Table 4-1 - Comparison of domestic elasticity of substitution values (Tracey & Wallach, 2003)**.**

State	Utility	Price Ratio	Elasticity	Voluntary or Mandatory	Experiment Year	Source
Five	5 Utilities	6.2:1 to 16:1	0.12	mandatory	1977–80	Caves ('84)
CA	PG&E	1.9:1 to 2.5:1	0.37	voluntary	1983–84	Caves ('89)
NJ	GPU	2.8:1 to 7.7:1	0.30	voluntary	1997	Braithwait ('00)
OK	Edmon Municipal	4.16:1	0.12	mandatory	1977–78	Huettner ('82)
WI	WPS	2:1 to 8:1	0.15	mandatory	1977	Park ('84)
IA	MPS	4.6:1	0.15-0.39	voluntary	1990–92	Baladi ('98)
WA	Puget Sound	1.18:1	0.53	voluntary	2001	Brattle Group ('01)

One further interesting point to note when reviewing the elasticities resulting from the application of variable pricing is the duration of peak pricing periods. (Boisvert, Cappers, Neenan, & Scott, 2004) found that elasticities decrease as the duration of these peak pricing increases, and attribute this to the increased difficulty/disruption associated with shifting loads over greater periods of time.

Another crucial aspect of demand elasticity - and one which is affected greatly by the social and behavioural aspects of energy consumption behaviour - is the variation in elasticity that occurs between otherwise similar consumers. This is explored by (Kirschen et al., 2000), who present five characteristic consumer types, each representing a different approach to DR. These consumer types are as follows:

1. Anticipating consumers.
2. Postponing consumers.
3. Flexible consumers.
4. Inflexible consumers.
5. Optimising consumers.

Kirschen conveys the differences between each consumer type using elasticity matrices, which plot the non-zero elasticity values of each consumer type for each half-hourly period of the day. An adaptation of these matrices is shown in Figure 4-3. In all of the five matrices pictured, diagonal lines (shown in red) represent self-elasticity, with any non-zero values above the diagonal indicating a willingness to bring forward consumption (in response to price variation) and those below the line indicating willingness to postpone consumption. These matrices show that anticipating consumers (matrix 1) i.e. those who only bring forward their demand, only have non-zero elasticity values above the diagonal line, while postponing consumers (matrix 2) have them only below. They also effectively demonstrate the differences between flexible (matrix 3) and inflexible (matrix 4) consumers. Lastly, the optimising consumer (matrix 5) can be seen to engage in highly responsive behaviour in order to take advantage of the very lowest prices, which usually occur very early in the morning or late at night. This effectively demonstrates the range of responses to variable pricing which can occur.

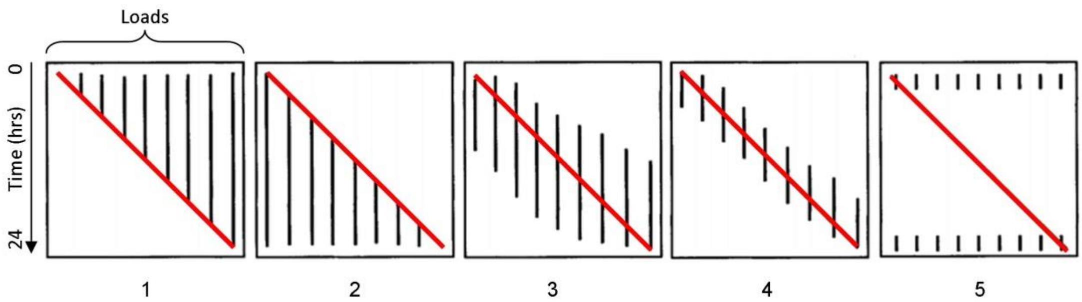


Figure 4-3 - Elasticity matrices of each of the five consumer types identified by (Kirschen et al., 2000)**.**

Variation in elasticity can also occur geographically, with attitudes and consumption patterns varying across different regions, climates and degree of urbanisation. This was examined by (Bernstein & Griffin, 2006), in their report for the American National Renewable Energy Laboratory. Their findings suggest that elasticity does vary at county, state and regional levels, particularly when it comes to residential demand. The regional level variations in residential electricity demand are shown below in Figure 4-4, which is taken directly from Bernstein and Griffin's report. It should be noted that additional factors (which were not/could not be accounted for) also impact upon elasticity values. These include cultural, educational and demographic issues.

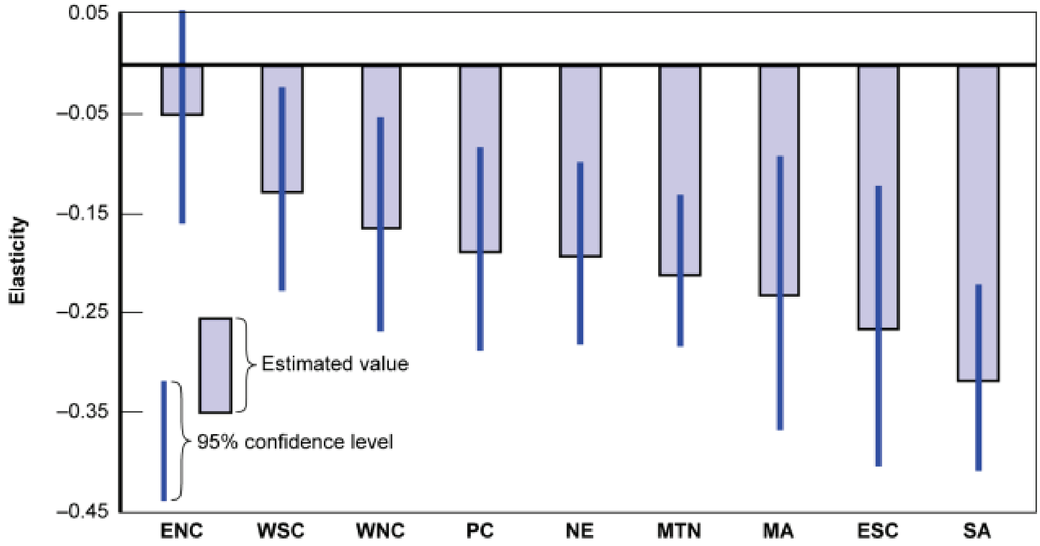


Figure 4-4 - Regional variations in domestic electricity demand, as presented by (Bernstein & Griffin, 2006)**.**

Similarly, though at a smaller scale, (Houthakker, Verleger, & Sheehan, 1974) also found a link between price elasticity and degree of urbanisation for both gasoline and domestic electricity use, concluding that “the short-run elasticities are smaller in absolute magnitude for the highly urbanised than for the less urbanised states”.

4.3.4 Towards extreme short-term elasticity

As discussed above, much of the literature on elasticity to date has tended to focus on a relatively long timeframe, with the term “short run” typically used to refer to elasticities over a timeframe of up to one year. However, the work of (Patrick & Wolak, 2001) is a noteworthy exception. In their 2001 study, Patrick and Wolak examined the response of consumers to price changes over a “within-day” timeframe i.e. prices that change over the course of a single day. This represents a marked departure from the bulk of the literature in that it focusses on what can effectively be seen as ‘extreme short-term’ CPED. It also represents a significant increase in the required level of engagement and involvement from consumers.

The increasing capability and cost-effectiveness of automation and metering technology discussed earlier in this chapter has facilitated a shifting of the responsibility for such regular engagement from consumers to technology. This enables a progression beyond dynamic tariffs to what Darby refers to as “dynamic demand”, and represents the far end of the spectrum when it comes to frequency of both price variation and advance notice to consumers (S. J. Darby, 2013).

Examining elasticity over such a short timeframe also alters the nature of the changes in demand in question. Over an extreme short-term period, a consumer’s response is likely to be more fleeting in nature, and less likely to be associated with lasting behavioural change (Lijesen, 2007). This lessens (but does not remove) the importance of the behavioural aspect of DR.

Given the lack of existing research into short-term demand elasticities mentioned above, coupled with the increasing capability of technology to facilitate complex and variable energy pricing strategies, there is a clearly identifiable need for more research into extreme short-term CPED, particularly within a domestic setting.

Kirschen at al. suggest that varying price in real time would represent the closest possible link between demand and supply. Such an approach would also represent the maximum exposure of consumers to financial risk (which many would be unlikely to be able to react to). As a result, the same authors are quick to point out that the scope for real-time price adjustment is limited (Kirschen et al., 2000). However, there is a growing consensus that the appropriate use of automation technology (as discussed previously in this chapter) is capable of facilitating a significant increase in elasticity by removing the need for direct consumer engagement. This is also particularly relevant in the extreme short term.

4.4 The Role of Variable Domestic Energy Pricing in SAHES

Having looked at the use of variable energy pricings strategies in a range of other contexts, it is now possible to consider how they might be applied at a domestic level within SAHES. Whilst this poses a number of significant challenges, this is still regarded as an area of considerable potential (McKenna et al., 2011).

4.4.1 Motivating factors

There are a number of aspects and characteristics which appear to make SAHES (and the communities in which they are deployed) well suited for the application of variable pricing. As identified by Owen and Ward, DR in general has historically been applied “where there are severe capacity or network constraints” (Owen & Ward, 2010). While the same cannot yet be said of variable energy pricing, the same principles apply.

Arguably the most important difference between the two applications is the motivation for applying variable energy pricing in the first place, and the desired outcomes of doing so. For the consumer, the motivation for participating in a variable pricing initiative (assuming that participation is voluntary) can be seen as being fairly similar for both grid-connected and stand-alone applications i.e. contributing to the efficient running of their energy network in exchange for potential financial benefit. It is, however, considered likely that the sense of community in remote and isolated areas, together with a greater knowledge and appreciation of energy supply and the importance of the role of consumers, will provide additional motivation.

For network/system operators, the motivation behind the use of variable energy pricing is likely to be very different within the context of stand-alone applications than it is for grid-connected ones.

4.4.2 Price variation drivers

As discussed in the previous chapter, the aim of DR in SAHES can be seen to be fundamentally different from conventional applications, with demand-supply matching taking precedence over reduction in peak demand. The same can also be said for variable pricing. In grid connected applications, the aim of promoting variable pricing has traditionally been to reduce peak demand during set times of the day, and a general flattening of the demand curve. As discussed in previous chapters, the aim within the context of stand-alone systems is to achieve demand-supply matching, which does not necessarily require either a reduction in demand levels or the flattening of the demand curve (although this remains a key point within the wider energy debate). This can be seen to negate one of the undesirable outcomes of some forms of variable pricing i.e. the failure to result in overall demand reduction, as noted by (Oldewurtel, Ulbig, Parisio, Andersson, & Morari, 2010; Owen & Ward, 2010). Perhaps most crucially for the case of SAHES, and as identified by (Saffre & Gedge, 2010), this approach also presents an opportunity to integrate “weather dependent generation”.

Pricing variations in SAHES are therefore likely to be based on the need for system balancing i.e. the minimisation of both energy surplus and energy deficit. Renewable energy supply profiles - or more specifically the balance between renewable energy supply and overall energy demand - are likely to serve as the main drivers for price variations in this context. Considering once again the comparison between the demand profile from a single dwelling and the supply from a small wind turbine, as discussed in the previous chapter and pictured in Figure 3-4, If price variation was based upon the demand-supply match shown, then the cost of energy would be highest between hours 18 and 22 (when the deficit is greatest) and lowest between hours 34 and 38 (when surplus is greatest).

By applying variable pricing in this way, both the energy storage and generation capacity required within the system shown could be reduced, and the levels of renewable energy penetration increased.

The concept of using the availability of energy as the basis for price variation is not new (Ulbig & Andersson, 2010). Indeed, (Dupont et al., 2012) identify that as quantities of renewable generation contributing to energy supply increases, variable pricing becomes more and more closely linked to RES (whilst maintaining links to wholesale costs etc.) However, the specific use of renewable energy generation as the basis for price variation presents a number of significant challenges. Firstly, the intermittent nature of renewable energy sources such as wind and solar technologies means that the energy balance (between renewable supply and demand) can only be predicted with any sort of accuracy on a short timescale. This means that advance notice of price variations cannot be issued a long time in advance. Since the unpredictability of the supply from renewable energy is carried over into the demand-supply match, which is itself the basis for energy price variations, the way in which the cost of energy fluctuates is also likely to be unpredictable. This lack of predictability makes responding to price variations much more difficult for consumers, as it requires short-term, reactive engagement. This appears to suggest that such an approach would likely require significant levels of technology to automate consumer response, thereby lessening the burden on consumers themselves.

Whilst the challenges associated with applying variable energy pricing within this context are significant, it should be noted that the impact and magnitude of variations in renewable supply can be lessened significantly through the scheduling of non-renewable forms of generation. Also, whilst reliance on intermittent forms of energy generation also places emphasis on the forecasting of renewable energy, it should be noted that some forms of renewable generation, such as tidal, wave and hydroelectric power, are less stochastic in nature and therefore more easily forecasted than others, such as solar and wind generation.

4.4.3 Demand elasticity

As discussed previously, the demand elasticity of consumers in SAHES is thought to differ from those in more urbanised, grid-connected areas of society due to the difference in understanding and appreciation of energy supply. This suggests that CPED values are likely to be higher in the remote and isolated communities in which SAHES are typically deployed. However, the extent to which this translates into variations in demand elasticity is unclear. This issue was the subject of research by Houthakker et al. in 1974, into the demand for gasoline and residential electricity (Houthakker et al., 1974). They found that, generally speaking, elasticities increased as the degree of urbanisation decreased.

The fact that remote and isolated communities are more likely to suffer from comparatively poor levels of energy reliability and security means that rates of voluntary participation in variable pricing strategies in these areas are likely to be higher. As discussed by Hill, voluntary participation (fuelled by willingness/desire to engage with variable pricing) can result in greater elasticity values (Hill, 1991). Awareness of environmental issues surrounding energy supply and consumption have also been found to translate into energy consumption behaviour, with Buryk et al. reporting a 10% reduction in demand from “environmentally conscious” consumers when exposed to dynamic pricing and provided with information as to the environmental and systemic benefits of DR (Buryk et al., 2015). Should such attitudes be more prominent in remote and isolate communities, this may well contribute to greater elasticities.

The literature does therefore appear to hint at a link between consumers in remote and isolated areas and a level of demand elasticity which is higher than more urban, grid-connected areas. This link is however in need of further investigation and verification, in order to establish its existence in more detail and to begin to quantify the resulting increase in elasticity. This will be addressed in more detail in the following chapter.

4.4.4 Stakeholder and market conditions

A final fundamental way in which variable energy pricing in stand-alone applications is likely to differ from grid-connected applications relates to the structure of the market and the roles of the key stakeholders.

In a conventional, grid-connected setup, the roles, responsibilities, regulation and spheres of influence of the various players have been reasonably well defined over time. The key stakeholders are:

- Energy consumers.

- Energy generators.
- System operators.
- Transmission Network Operators (TNO's).
- Distribution Network Operators (DNO's).
- Utilities.
- The market regulator.

As discussed previously, the integration of renewable and distributed energy into this set up has presented a number of technical and regulatory challenges (Driesen & Belmans, 2006; Lopes, Hatziargyriou, Mutale, Djapic, & Jenkins, 2007; Luo, Ault, & Galloway, 2010).

However, in SAHES applications, a number of factors exist which negate or remove some of these issues. Firstly, the very fact that the energy system (and its consumers) is physically separated from the grid means that a number of the traditional stakeholders are removed from the equation, such as TNO's, regulators and even DNO's.

The second major distinguishing factor is the potential for community ownership of SAHES. As discussed in Chapter 2, this can result in the local community acting as consumers, generators, owners and operators. This fundamentally changes the way in which the system can be run.

Conventionally, the sale of energy within distributed energy systems is facilitated using an 'auction' type negotiation process (Alibhai, Gruver, Kotak, & Sabaz, 2004). This approach is based on two key assumptions:

1. Energy consumers wish to have their energy demands met at minimum expense.

2. Energy generators wish to maximise their profits by ensuring they receive the highest price possible for the energy generated.

However, the latter of these assumptions becomes redundant if both parties are one and the same i.e. the consumers share collective ownership of the energy system and its components, or the energy company exists to serve the community and not to generate profit. As such, the second of the priority assumptions above can be altered as follows:

2. Energy system operators wish to secure sufficient revenue as to ensure the ability of the system to meet the current and future energy needs of consumers.

In such cases, marked differences also exist in terms of desired financial outcomes. Instead of the maximisation of profit and minimisation of the need for system maintenance and expenditure, the goal of community-owned systems is more likely to be the continued financial sustainability of the system and the supply of affordable energy to the consumers it serves, with project revenue more likely to be reinvested either locally or within the renewable energy sector (Mcewen, Harnmeijer, Harnmeijer, & Bhopal, 2012). It is thought that the combination of these factors is likely to result in a higher degree of voluntary participation when it comes to the application of variable energy pricing.

It should also be noted that market-based barriers facing variable pricing in SAHES can also be extended to include those facing renewable energy deployment in general. As noted by Painuly, these include the favourable treatment currently given to conventional generation, the taxation of renewables and the lack of consideration of externalities such as pollution from conventional generation and the aforementioned benefits of renewable generation, upon pricing (Painuly, 2001). In the years since Painuly's article the disparity between the subsidisation of fossil fuel and renewable generation has only increased (particularly in the UK, where cuts to Feed In Tariffs and tax breaks to the oil industry have been the main contributors).

4.5 Conclusions

This chapter has reviewed variable energy pricing from both a theoretical and a practical perspective, and has also identified a number of key issues relating to its use.

It is clear that the role of the domestic consumer in future energy systems is a more active one than under the prevailing centralised model, with consumer engagement via DR having a vital role to play. The literature reviewed suggests that variable energy pricing is an effective way of promoting DR, with recent decades seeing the gradual expansion of variable energy pricing from the industrial and commercial sector into the domestic sector.

Consumer price elasticity of demand has been identified as a key concept, as it governs the extent to which consumers either curtail or shift their energy consumption. When it comes to the use of variable energy pricing in a domestic context, one key issue to emerge from the literature is the importance of the differences which exist between long-term and short-term elasticity, such as the tendency for elasticities to be higher in the long-term than in the short-term. This stems from the differences in how changes in demand are achieved, with appliance efficiency, behavioural changes and cultural factors all affecting the impact and sustainability of changes in demand.

One area which receives comparatively little coverage in the existing literature is the quantification of domestic demand elasticity over the extreme short-term. As a result, very little is known of consumer attitudes and responses to “within-day” price variations. Demand changes which occur within this timeframe are highly relevant to

DR, particularly within the context of SAHES. The next chapter will investigate this issue further.

The literature reviewed also emphasised that consumers can only respond to energy price fluctuations to which they are exposed, with Kirschen et al asserting that “Consumers that are exposed to a large volatility in prices will definitely pay more attention to their demand profile than those who buy on a flat tariff” (Kirschen et al., 2000). This supports the view that the current energy supply model is conducive to low elasticities, and in turn suggests that there is considerable room for current elasticity levels to be increased.

However, more research is also required into consumer willingness to accept variable pricing and into domestic attitudes towards both DR in general and the use of technology to facilitate it. This includes attitudes towards automation technology, about which relatively little is known.

Of all the areas of research reviewed in this chapter, the role of automation and enabling technology was found to be developing the fastest. This is indicative of the considerable potential and rapidly increasing capability of such technologies, and their ability to support both energy pricing strategies which deal with reduced timesteps, and more complex relationships between consumers and their energy systems.

This chapter has also examined the potential role of variable domestic energy pricing specifically within SAHES. While the desired outcomes and the basis for price variation in this context may differ from conventional/traditional forms of variable pricing, a number of characteristics of remote and isolated communities and SAHES were identified which suggest that they would be ideal for the introduction of variable energy pricing. However, limited evidence was found to support the idea that demand elasticity decreases as urbanisation decreases. Both of these areas are of particular relevance to this project, and will be examined in more detail in the following chapter.

4.6 References for Chapter 4

Aalami, H. A., Moghaddam, M. P., & Yousefi, G. R. (2010). Demand response modeling considering interruptible/curtailable loads and capacity market programs. *Applied Energy*, *87*(1), 243–250.

Albadi, M. H., & El-Saadany, E. F. (2007). Demand response in electricity markets: An overview. In *IEEE power engineering society general meeting* (Vol. 2007, pp. 1–5).

Alibhai, Z., Gruver, W. A., Kotak, D. B., & Sabaz, D. (2004). Distributed coordination of micro-grids using bilateral contracts. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on* (Vol. 2, pp. 1990–1995 vol.2). doi:10.1109/ICSMC.2004.1399985

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and Energy Economics*, *33*(4), 820–842. Retrieved from http://www.sciencedirect.com/science/article/pii/S092876551100042X

Aubin, C., Fougère, D., Husson, E., & Ivaldi, M. (1995). Real-time pricing of electricity for residential customers: Econometric analysis of an experiment. *Journal of Applied Econometrics*, *10*(S1), S171–S191. doi:10.1002/jae.3950100510

Bernstein, M. A., & Griffin, J. (2006). *Regional Differences in the Price-Elasticity of Demand for Energy*. Retrieved from http://www.nrel.gov/docs/fy06osti/39512.pdf

Berry, L. (1993). A review of the market penetration of US residential and commercial demand-side management programmes. *Energy Policy*, *21*(1), 53–67. Retrieved from http://www.sciencedirect.com/science/article/pii/030142159390208W

Biviji, M. A., Wang, W. M., Ostrowski, J., & Wang, J. (2012). Price elasticity of electricity demand for various dynamic rate programs. *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*. doi:10.1109/ISGT.2012.6175696

Bohi, D. R., & Zimmerman, M. B. (1984). An update on econometric studies of energy demand behavior. *Annual Review of Energy*, *9*(1), 105–154.

Boisvert, R., Cappers, P., Neenan, B., & Scott, B. (2004). Industrial and commercial customer response to real time electricity prices. *December, Available Online at Http://eetd. Lbl. gov/ea/EMS/drlm-Pubs. Html*.

Borenstein, S. (2005). The long-run efficiency of real-time electricity pricing. *The Energy Journal*, 93–116. Retrieved from http://www.ucei.berkeley.edu/PDF/csemwp133R.pdf

Borenstein, S., Jaske, M., & Rosenfeld, A. (2002). Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. Retrieved from http://www.escholarship.org/uc/item/11w8d6m4

Bradley, P., Leach, M., & Torriti, J. (2013). A review of the costs and benefits of demand response for electricity in the UK. *Energy Policy*, *52*, 312–327. doi:10.1016/j.enpol.2012.09.039

Braithwait, S. (2000). Residential TOU Price Response in the Presence of Interactive Communication Equipment. In A. Faruqui & K. Eakin (Eds.), *Pricing in Competitive Electricity Markets SE - 22* (Vol. 36, pp. 359–373). Springer US. doi:10.1007/978-1-4615-4529-3_22

Buryk, S., Mead, D., Mourato, S., & Torriti, J. (2015). Investigating preferences for dynamic electricity tariffs: The effect of environmental and system benefit disclosure. *Energy Policy*, *80*, 190–195. doi:10.1016/j.enpol.2015.01.030

Caves, D. W., & Christensen, L. R. (1980). Econometric analysis of residential time-of-use electricity pricing experiments. *Journal of Econometrics*, *14*(3), 287–306. doi:10.1016/0304-4076(80)90029-9

Clastres, C. (2011). Smart grids: Another step towards competition, energy security and climate change objectives. *Energy Policy*, *39*(9), 5399–5408. Retrieved from http://www.sciencedirect.com/science/article/pii/S030142151100396X

Conejo, A. J., Morales, J. M., & Baringo, L. (2010). Real-Time Demand Response Model. *Smart Grid, IEEE Transactions on*, *1*(3), 236–242. doi:10.1109/TSG.2010.2078843

Dahl, C., & Sterner, T. (1991). Analysing gasoline demand elasticities: a survey. *Energy Economics*, *13*(3), 203–210.

Darby, S. (2006). *The effectiveness of feedback on energy consumption: a review for DEFRA of the literature on metering, billing and direct displays*. Retrieved from http://powerwatch.biz/site/wp-content/uploads/2012/02/smart-metering-report.pdf

Darby, S. J. (2013). Load management at home: advantages and drawbacks of some “active demand side” options. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy* , *227* (1), 9–17. doi:10.1177/0957650912464623

Darby, S. J., & McKenna, E. (2012). Social implications of residential demand response in cool temperate climates. *Energy Policy*, *49*(0), 759–769. Retrieved from http://www.sciencedirect.com/science/article/pii/S0301421512006076

David, A. K., & Li, Y. Z. (1991). Consumer rationality assumptions in the real time pricing of electricity. In *Advances in Power System Control, Operation and Management, 1991. APSCOM-91., 1991 International Conference on* (pp. 391–396 vol.1). Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=154105

David, A. K., Nutt, D. J., Chang, C. S., & Lee, Y. C. (1986). The variation of electricity prices in response to supply-demand conditions and devices for consumer interaction. *International Journal of Electrical Power & Energy Systems*, *8*(2), 101–114. doi:10.1016/0142-0615(86)90004-9

Devine-wright, P., & Wiersma, B. (2013). Opening up the “local” to analysis: exploring the spatiality of UK urban decentralised energy initiatives. *A Report on Community Renewable Energy in Scotland - SCENE Connect Report*, (March), 37–41. doi:10.1080/13549839.2012.754742

Di Giorgio, A., & Pimpinella, L. (2012). An event driven Smart Home Controller enabling consumer economic saving and automated Demand Side Management. *Applied Energy*, *96*(0), 92–103. Retrieved from http://www.sciencedirect.com/science/article/pii/S0306261912001183

Ding, Y., Nyeng, P., Østergaard, J., Trong, M. D., Pineda, S., Kok, K., … Grande, O.

S. (2012). Ecogrid EU – A Large Scale Smart Grids Demonstration of Real Time Market-based Integration of Numerous Small DER and DR. In *2012 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe)* (pp. 1–7).

Doostizadeh, M., & Ghasemi, H. (2012). A day-ahead electricity pricing model based on smart metering and demand-side management. *Energy*, *46*(1), 221–230. Retrieved from http://www.sciencedirect.com/science/article/pii/S0360544212006603

Downing, P., & Icaro Consulting. (2009). *Understanding Consumer Attitudes to "Sustainable Community Infrastructure."* Retrieved from http://www.ukgbc.org/resources/publication/report-understanding-consumer-attitudes-sustainable-community-infrastructure

Driesen, J., & Belmans, R. (2006). Distributed generation: challenges and possible solutions. *Power Engineering Society General Meeting, 2006. IEEE*. doi:10.1109/PES.2006.1709099

Dupont, B., De Jonghe, C., Kessels, K., & Belmans, R. (2011). Short-term consumer benefits of dynamic pricing. In *Energy Market (EEM), 2011 8th International Conference on the European* (pp. 216–221). doi:10.1109/EEM.2011.5953011

Dupont, B., Tant, J., & Belmans, R. (2012). Automated residential demand response based on dynamic pricing. In *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on* (pp. 1–7). doi:10.1109/ISGTEurope.2012.6465806

Ericson, T. (2009). Direct load control of residential water heaters. *Energy Policy*, *37*(9), 3502–3512. doi:10.1016/j.enpol.2009.03.063

Faria, P., & Vale, Z. (2011). Demand response in electrical energy supply: An optimal real time pricing approach. *Energy*, *36*(8), 5374–5384. Retrieved from http://www.sciencedirect.com/science/article/pii/S036054421100435X

Faruqui, A., & George, S. (2005). Quantifying Customer Response to Dynamic Pricing. *The Electricity Journal*, *18*(4), 53–63. doi:10.1016/j.tej.2005.04.005

Faruqui, A., & George, S. S. (2002). The Value of Dynamic Pricing in Mass Markets. *The Electricity Journal*, *15*(6), 45–55. doi:10.1016/S1040-6190(02)00330-5

Filippini, M. (1995). Electricity demand by time of use An application of the household AIDS model. *Energy Economics*, *17*(3), 197–204. doi:10.1016/0140-9883(95)00017-O

Gillingham, K., Newell, R. G., Sweeney, J., Brennan, T., Auffhammer, M., Howarth, R., & Cullenward, D. (2009). Energy Efficiency Economics and Policy. *Annual Review of Resource Economics*, *1*, 597–620. Retrieved from http://www.nber.org/papers/w15031.pdf

Hammerstrom, D., & Ambrosio, R. (2007). *Pacific Northwest GridWise^{TM} Testbed Demonstration Projects; Part 1: Olympic Peninsula Project*. *… Peninsula Project*. Retrieved from http://sites.energetics.com/MADRI/toolbox/pdfs/pricing/pnnl_2007_pacific_nw_gridwise_olympic_peninsula.pdf

He, H. Z., & Kua, H. W. (2013). Lessons for integrated household energy conservation policy from Singapore's southwest Eco-living Program. *Energy Policy*, *55*, 105–116. doi:10.1016/j.enpol.2012.10.067

Herter, K. (2007). Residential implementation of critical-peak pricing of electricity. *Energy Policy*, *35*(4), 2121–2130. doi:http://dx.doi.org/10.1016/j.enpol.2006.06.019

Herter, K., McAuliffe, P., & Rosenfeld, A. (2007). An exploratory analysis of California residential customer response to critical peak pricing of electricity. *Energy*, *32*(1), 25–34.

Herter, K., & Wayland, S. (2010). Residential response to critical-peak pricing of electricity: California evidence. *Energy*, *35*(4), 1561–1567. doi:10.1016/j.energy.2009.07.022

Hill, L. J. (1991). Residential time-of-use pricing as a load management strategy: Effectiveness and applicability. *Utilities Policy*, *1*(4), 308–318. Retrieved from http://www.sciencedirect.com/science/article/pii/095717879190071C

Holland, S. P., & Mansur, E. T. (2006). The short-run effects of time-varying prices in competitive electricity markets. *ENERGY JOURNAL-CAMBRIDGE MA THEN CLEVELAND OH-*, *27*(4), 127. Retrieved from http://www.ucei.berkeley.edu/PDF/csemwp143r.pdf

Houthakker, H. S. (1951). Electricity Tariffs in Theory and Practice. *The Economic Journal*, *61*(241), 1–25 CR – Copyright © 1951 Royal Economic So. doi:10.2307/2226608

Houthakker, H. S., Verleger, P. K., & Sheehan, D. P. (1974). Dynamic Demand Analyses for Gasoline and Residential Electricity. *American Journal of Agricultural Economics* , *56* (2), 412–418. doi:10.2307/1238776

Kaplan, S. (2000). New Ways to Promote Proenvironmental Behavior: Human Nature and Environmentally Responsible Behavior. *Journal of Social Issues*, *56*(3), 491–508. Retrieved from http://dx.doi.org/10.1111/0022-4537.00180

Keane, D. M., & Goett, A. (1988). Voluntary residential time-of-use rates: lessons learned from Pacific Gas and Electric Company's experiment. *Power Systems, IEEE Transactions on*, *3*(4), 1764–1768.

Kim, J.-H., & Shcherbakova, A. (2011). Common failures of demand response. *Energy*, *36*(2), 873–880. doi:10.1016/j.energy.2010.12.027

King, C. S., & Chatterjee, S. (2003). Predicting California Demand Response - How do customers react to hourly prices? *Public Utilities Fortnightly*, (July 1), 27–32. Retrieved from http://www.americanenergyinstitutes.org/research/CaDemandResponse.pdf

Kirschen, D. S., Strbac, G., Cumperayot, P., & de Paiva Mendes, D. (2000). Factoring the elasticity of demand in electricity prices. *Power Systems, IEEE Transactions on*, *15*(2), 612–617. doi:10.1109/59.867149

Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy Economics*, *29*(2), 249–258. doi:http://dx.doi.org/10.1016/j.eneco.2006.08.008

Lopes, J. A. P., Hatziargyriou, N., Mutale, J., Djapic, P., & Jenkins, N. (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric Power Systems Research*, *77*(9), 1189–1203.

Lujano-Rojas, J. M., Monteiro, C., Dufo-López, R., & Bernal-Agustín, J. L. (2012). Optimum residential load management strategy for real time pricing (RTP) demand response programs. *Energy Policy*, *45*, 671–679. doi:10.1016/j.enpol.2012.03.019

Luo, T., Ault, G., & Galloway, S. (2010). Demand Side Management in a Highly Decentralized Energy Future. In *Universities Power Engineering Conference*.

Marzband, M., Sumper, A., Ruiz-Álvarez, A., Domínguez-García, J. L., & Tomoiagă, B. (2013). Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets. *Applied Energy*, *106*, 365–376. doi:10.1016/j.apenergy.2013.02.018

Mcewen, N., Harnmeijer, A., Harnmeijer, J., & Bhopal, V. (2012). *A Report on Community Renewable Energy in Scotland - SCENE Connect Report*. Retrieved from http://library.uniteddiversity.coop/REconomy_Resource_Pack/Community_Energy/A_report_on_Community_Energy_in_Scotland.pdf

McKenna, E., Ghosh, K., & Thomson, M. (2011). Demand response in low-carbon power systems: a review of residential electrical demand response projects. In *The 2nd International Conference on Microgeneration and Related Technologies* (Vol. 3). Glasgow. doi:10.2307/302397

Mohsenian-Rad, A.-H., & Leon-Garcia, A. (2010). Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments. *Smart Grid, IEEE Transactions on*, *1*(2), 120–133. doi:10.1109/TSG.2010.2055903

Newsham, G. R., & Bowker, B. G. (2010). The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, *38*(7), 3289–3296. doi:10.1016/j.enpol.2010.01.027

Ofgem. (2013). The state of the market for customers with dynamically teleswitched meters. Retrieved from https://www.ofgem.gov.uk/ofgem-publications/82288/state-market-customers-dynamically-teleswitched-meters.pdf

ohmconnect. (2015). ohmconnect. Retrieved November 5, 2015, from www.ohmconnect.com

Oldewurtel, F., Ulbig, A., Parisio, A., Andersson, G., & Morari, M. (2010). Reducing peak electricity demand in building climate control using real-time pricing and model predictive control. In *Decision and Control (CDC), 2010 49th IEEE Conference on* (pp. 1927–1932). doi:10.1109/CDC.2010.5717458

Opinion Leader. (2009). *Ofgem Consumer First Panel - Research Findings from the Third Events*. Retrieved from https://www.ofgem.gov.uk/ofgem-publications/57576/ofgem-panel-third-events-report-final.pdf

Owen, G., & Ward, J. (2010). Smart tariffs and household demand response for Great Britain. *Sustainability First, London*, 2010. Retrieved from http://www.sustainabilityfirst.org.uk/docs/2010/Sustainability First - Smart Tariffs and Household Demand Response for Great Britain - Final - March 2010.pdf

Painuly, J. P. (2001). Barriers to renewable energy penetration; a framework for analysis. *Renewable Energy*, *24*(1), 73–89.

Patrick, R. H., & Wolak, F. A. (2001). *Estimating the Customer-Level Demand for Electricity Under Real-Time Market Prices* (No. 8213). Cambridge, MA. Retrieved from http://www.nber.org/papers/w8213.pdf

Radio Teleswitch Services. (2016). Radio Teleswitching: History. Retrieved May 16, 2016, from http://79.171.36.154/rts/history.asp

Saffre, F., & Gedge, R. (2010). Demand-Side Management for the Smart Grid.

Network Operations and Management Symposium Workshops (NOMS Wksps), 2010 IEEE/IFIP. doi:10.1109/NOMSW.2010.5486558

Salies, E. (2013). Real-time pricing when some consumers resist in saving electricity. *Energy Policy*, *59*(0), 843–849. doi:http://dx.doi.org/10.1016/j.enpol.2013.04.050

Samadi, P., Mohsenian-Rad, A.-H., Schober, R., Wong, V. W. S., & Jatskevich, J. (2010). Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart Grid. *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*. doi:10.1109/SMARTGRID.2010.5622077

Sioshansi, R., & Short, W. (2009). Evaluating the impacts of real-time pricing on the usage of wind generation. *Power Systems, IEEE Transactions on*, *24*(2), 516–524.

Spees, K., & Lave, L. B. (2007). Demand Response and Electricity Market Efficiency. *The Electricity Journal*, *20*(3), 69–85. doi:10.1016/j.tej.2007.01.006

Strong, L., & Which? (2014). Wrestling with trust. In *Energy Systems Conference 2014*.

Taylor, L. D. (1975). The demand for electricity: a survey. *The Bell Journal of Economics*, 74–110.

The Electricity Council. (1982). *Electricity Supply in the UK: A chronology* (3rd Editio.). London: The Electricity Council.

Ton, D., Biviji, M. A., Nagypal, E., & Wang, J. (2013). Tool for determining price elasticity of electricity demand and designing dynamic price program. *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*. doi:10.1109/ISGT.2013.6497848

Torriti, J. (2012). Price-based demand side management: Assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy. *Energy*, *44*(1), 576–583. Retrieved from http://www.sciencedirect.com/science/article/pii/S0360544212004409

Torriti, J., Hassan, M. G., & Leach, M. (2010). Demand response experience in Europe: Policies, programmes and implementation. *Energy*, *35*(4), 1575–1583. doi:http://dx.doi.org/10.1016/j.energy.2009.05.021

Torriti, J., & Leach, M. (2012). Making the least active pay: a simulation of rewards and penalties under Demand Side Participation programs. *International Journal of Green Energy*, *9*(7), 584–596. Retrieved from http://centaur.reading.ac.uk/23569/

Tracey, B., & Wallach, J. (2003). *Peak-Shaving/Demand Response Analysis: Load-Shifting by Residential Customers*. Retrieved from http://sedc-coalition.eu/wp-content/uploads/2011/05/Tracey-Load-Shifting-by-Residential-Customers-2003.pdf

Ulbig, A., & Andersson, G. (2010). Towards variable end-consumer electricity tariffs reflecting marginal costs: A benchmark tariff. In *Energy Market (EEM), 2010 7th International Conference on the European* (pp. 1–6). doi:10.1109/EEM.2010.5558777

Wolak, F. A. (2007). *Residential customer response to real-time pricing: The anaheim critical peak pricing experiment*. *Center for the Study of Energy Markets Working Paper Series*. Retrieved from http://eprints.cdlib.org/uc/item/3td3n1x1

Chapter 5: Energy Consumption Attitudes Survey

5.1 Energy Consumption Attitudes Survey

The previous chapters have reviewed the literature on domestic energy consumption, behavioural change and the use of variable energy pricing to promote DR. However, in order to gain a more in-depth understanding of how DR is viewed by domestic consumers, and specifically those who live in remote or isolated communities (such as those served by SAHES) further information is required.

This chapter presents a consumer survey which was intended to gauge consumer attitudes towards energy consumption and in particular to gauge receptiveness towards the concept of DR and the use of technology to aid in its implementation. This survey therefore addresses two of the major outcomes of the literature review conducted in previous chapters and also addresses the lack of knowledge surrounding CPED in the extreme short-term, and consumer attitudes towards the technology which could help facilitate it. In doing so, the survey also compares the responses of consumers living in remote and isolated communities to those from more urbanised areas, in order to identify any differences in attitudes which may exist.

The results of the survey not only supplement and verify some of the assertions made in the literature, but also provide a means of verifying some of the assumptions made by the author regarding attitudes towards DR amongst domestic consumers, and the motivations behind them.

5.2 Survey Design

The primary objectives identified at the outset of the survey development process were as follows:

- To gauge the attitudes of domestic energy consumers towards the concept of DR and the use of enabling technology, including an examination of the motivating factors behind receptive attitudes towards demand flexibility.
- To obtain sufficient data to facilitate a meaningful comparison of the attitudes of consumers living in urban and suburban communities with those living in rural and remote communities.

The desired outcome of the survey was a set of results that could usefully inform the discussion surrounding the future deployment of DR, the use of enabling technology and the use of financial incentives to elicit DR among domestic consumers.

5.2.1 Sampling methodology

The selection of an appropriate sampling methodology for the survey initially posed a number of significant challenges and requirements. Firstly it was deemed essential to ensure that a sufficient number of responses from rural and remote/isolated communities were obtained in order to facilitate a meaningful comparison with responses from more urbanised areas. As these communities represent a small proportion of the general population, this required a more targeted, non-probability sampling approach. In addition, gaining access to small remote and isolated communities presented a challenge, particularly given the aforementioned need to maximise response rates in these areas.

Having considered the above requirements and constraints, a ‘chain-referral’ methodology was selected as being most appropriate for the study. This method (also referred to as ‘snowball’ sampling) presents a cost and time effective way of utilising existing social networks in order to maximise response rates, particularly in targeted areas (Biernacki & Waldorf, 1981). This also allowed specific consumer types to be targeted in addition to wider and more randomised chain-referral processes. Whilst this effectively limits the wider representativeness of the findings, it was seen as a necessary step in order to satisfy the requirement for sufficient responses from all consumer types.

In an attempt to combat the likelihood of sampling bias - which could occur if the distribution of the survey was limited to like-minded respondents (such as those who are active in energy conservation or the promotion of renewable energy etc.) rural and remote/isolated communities were approached through a total of 125 local development trusts, via the Development Trust Association Scotland (DTAS, 2014). Development trusts were seen as an appropriate initial access point in such communities, given their active roles within communities, extensive and inclusive social networks, and crucially their lack of stated bias towards the themes and content of the survey itself, thus limiting the potential for sampling bias. This was supplemented by a broader social media campaign which circulated the survey more widely through urban and suburban respondents (although some of the development trusts did encompass suburban areas). This also served to diversify the profile and characteristics of respondents.

The survey was launched on May 6th 2014, and was initially scheduled to close to new respondents on June 30th. However, in order to allow the chain of referral required to disseminate the survey to develop fully, the closing date was later extended to the 13th of July 2014, giving a total active time of around 9 weeks. Participation was limited to those who were aged 16 and over, and who were permanent UK residents.

5.2.2 Survey design and development

The survey underwent an extensive period of testing and development in an attempt to ensure that the content, format, structure and wording of the questions were as clear and as easy to understand as possible. Special effort was made to ensure that consumers with little or no prior knowledge of energy issues (and the associated vocabulary) could understand and answer the questions effectively. An internal testing panel consisting of researchers (from both related and unrelated fields) and selected members of the public were used to finalise the wording and structure of the survey and its questions, which allowed any issues to be identified and addressed before the survey was launched.

The survey was developed using the Qualtrics Research Suite (Qualtrics, 2014). This program provided access to an appropriate range and number of questions, and to utilise display logic to structure each individual survey based on responses. By selecting a web-based surveying method, the research team were able to distribute the survey quickly and cost-effectively by utilising email and social media, and to maximise the ease and speed of participation for respondents. The web-based surveying method carries with it certain limitations (which are discussed in more detail in section 5.4.3), but was identified as being most appropriate for a survey of this kind.

The survey consisted of three main sections, each covering different aspects: ‘About your home’, ‘Energy Attitudes’ and ‘Your attitude towards Demand Response’. The first of these sections gathered information about the respondent’s household, such as postcode, the number of permanent occupants, primary heating fuel and energy tariff type. It also asked respondents to define whether they lived in an urban, suburban, rural or remote/isolated community (the provision of postcode information was also used to help corroborate responses). The second section aimed to gain an understanding of respondents’ views on wider energy issues, and included an element of self-evaluation relating to consumption and knowledge/understanding of energy issues. Finally, the last section outlined the concept of DR to respondents, and gauged their willingness (or otherwise) to adapt their energy consumption in the way described, as well as their motivations for doing so. This section also gauged attitudes towards the use of technology to aid in the process. The full wording of the survey can be found in Appendix A.

5.3 Survey Results

The survey was successfully completed by 228 respondents, primarily from within Scotland, but also within parts of England. Figure 5-1 shows a map of respondent locations within Scotland, and highlights the success of the efforts included as part of the sampling methodology to include a broad range of community locations in the study. The overall mean survey duration was 10 minutes, but 55% of respondents completed the survey in 5 minutes or less.

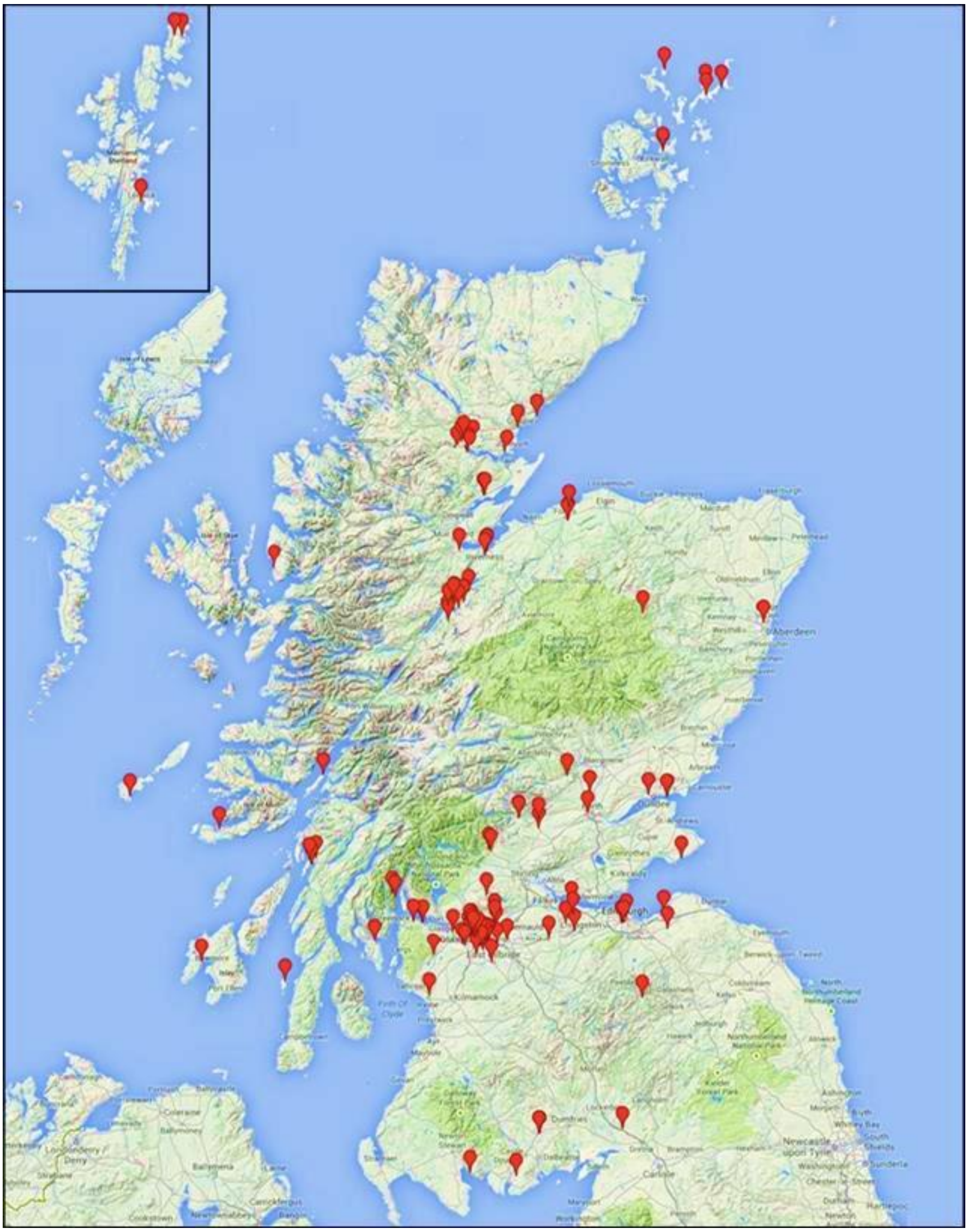


Figure 5-1 - Map showing the location of Scottish survey respondents.

The rest of this section summarises the results of the survey itself, and is broken down into the three main sections of the survey.

5.3.1 Respondent household information

The first section of the survey was used to gather data on the respondent and their household characteristics, which could later be used in the comparison between attitudes in various community types and locations.

The effort made to target consumers in rural and remote communities as part of the sampling methodology is reflected in the distribution of respondent community types, shown below in Figure 5-25. Whilst far from being representative of the wider UK population as a whole, this distribution provides a suitable basis for comparing the responses and attitudes of energy consumers from these different community types.

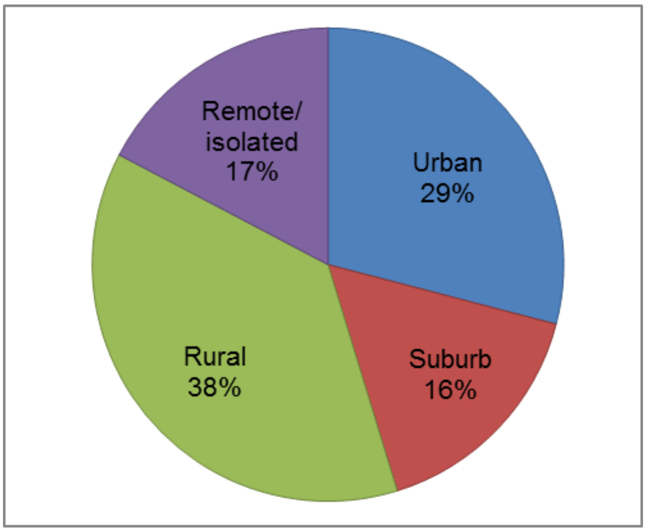


Figure 5-25 - Respondent community types.

Respondents were asked to specify the primary source of heating used in their homes. The most common responses included mains gas which accounted for 46% of responses. Liquid fossil fuels (such as red diesel, fuel oil and Liquid Petroleum Gas) was selected by 16% of respondents, but was limited to those in rural and remote/isolated communities, as was the use of wood fuel (10.7% of respondents), heat pumps (3.9%) and bottled gas (1.7%). The use of electric heating (15.7%) was spread across urban, rural and isolated/remote communities.

Respondents were then asked to specify the type of energy tariff used by their household to pay for energy, and were given a list of the most commonly used options. A link to a consumer information web page published by UK consumer group ‘Which?’ was supplied in order to provide clarification of the various tariff types and how they work (Which?, 2014). Despite this however, the results received suggest an element of confusion or a lack of understanding when it comes to energy tariffs, with some providing a definition using the “Other (please specify)” text input facility that matched one of the provided options. This apparent lack of understanding is also reflected by the fact that 18.6% of respondents answered “Don’t know”. Of the 10.7% of respondents which selected “Other (please specify)” 7 specified “standard” or similar. This is again indicative of a lack of knowledge and understanding when it comes to tariffs and billing. 6 respondents (3.4%) reported using some variant of a ‘total control’ type tariff, which is a multi-metered means of supplying electric heating (similar to Economy 7/10 tariffs) whilst keeping other domestic consumption metered separately. Fixed and dual fuel tariffs were the most popular answers, with each receiving 20% of responses. 11.3% of respondents reported using online-only tariffs. 8% of respondents reported using Economy 7 or Economy 10 tariffs, which allow consumers to make use of cheaper electricity at night. The 2.8% of respondents who reported using a “green” energy tariff were spread across all 4 community types. A full breakdown of these responses is shown in Table 5-1.

Table 5-1 - Breakdown of respondent tariff use.

Tariff Type	*Total Responses*	Breakdown of responses by community type			
		Urban	Suburban	Rural	Remote/ Isolated
Dual fuel	*35*	16	10	8	1
Capped	*5*	0	0	5	0
Fixed	*36*	8	3	18	7
Online	*20*	8	5	5	2
Economy 7 / 10	*14*	4	0	4	6
Prepayment meters	*9*	4	1	3	1
Green	*5*	1	1	2	1
Independent gas transporter	*1*	0	0	1	0
Social energy tariff	*0*	0	0	0	0
Other (please specify)	*19*	2	3	9	5
Don't know	*33*	9	5	11	8
TOTAL	*177*	*52*	*28*	*66*	*31*

5.3.2 Energy Attitudes

This section of the survey was intended to gauge the attitudes of respondents towards energy issues in general, and included some self-reporting questions which provided some insight into how respondents tend to view their own energy consumption behaviour.

Respondents were asked to rate the importance of energy supply in comparison to other social issues such as education, healthcare and the economy. The results, shown in Figure 5-3, show that “Middle priority” and “High priority” were the most popular answers.

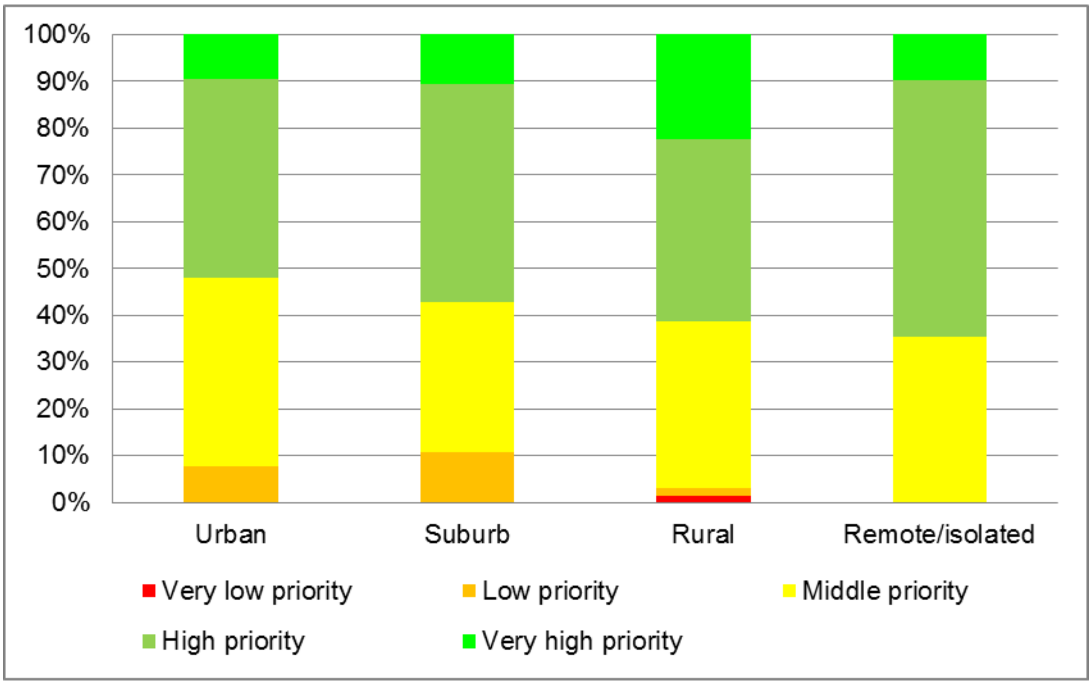


Figure 5-3 - Prioritisation of energy supply according to respondent community location.

Figure 5-3 also shows that rural communities had the highest occurrence of “Very high priority”, and a general downward trend can be seen in the number of “Middle priority” to “Very low priority” answers as community type becomes less urbanised.

Respondents were asked to define the extent to which they consider their energy consumption in everyday life. The results, as shown in Figure 5-4, clearly show that the frequency of consideration of energy consumption increases as urbanisation decreases. This creates an interesting contrast with the findings of (Druckman & Jackson, 2008), who found consumers in remote areas were more likely to consume greater amounts of energy than those in urbanised areas.

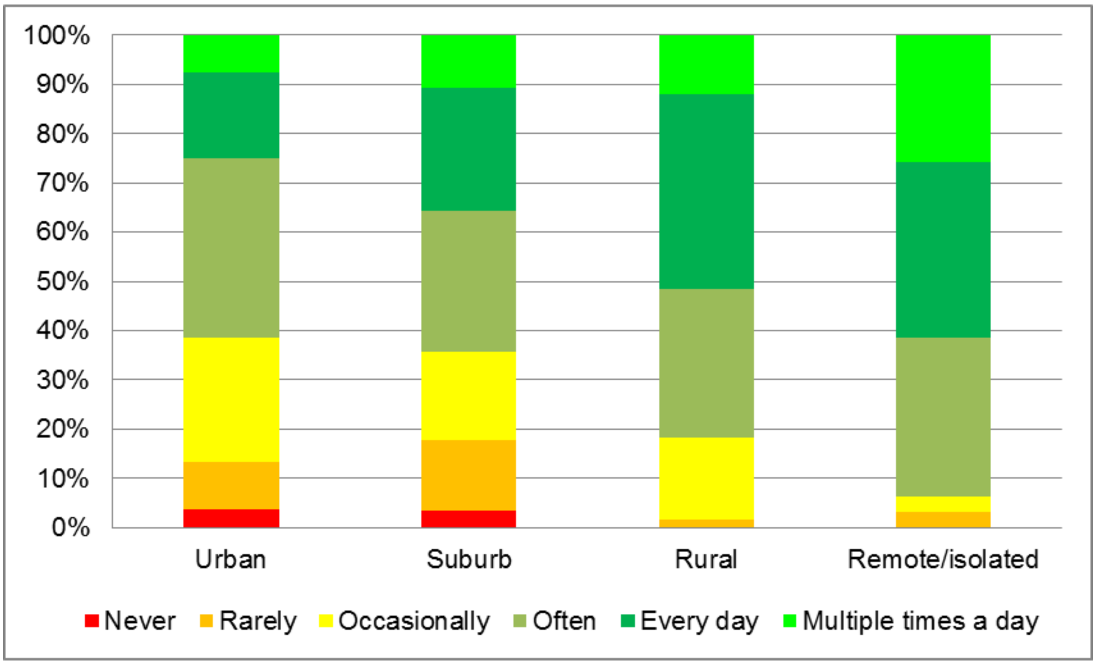


Figure 5-4 - Extent to which energy consumption is considered in everyday life.

Respondents were asked to rate their own knowledge and understanding of energy issues, including “understanding and appreciation of the energy supply system, how it works and the challenges associated with it”, relative to an un-specified average. As no information was provided regarding what is meant by ‘average’, respondents are expressing their own evaluation of their knowledge and understanding.

The results, shown in Figure 5-5, show that the majority of respondents regard their knowledge and understanding to be above average. There is a clear increase in the variation in responses to this question amongst respondents from more urban/centralised communities. While urban and suburban areas have the only occurrences of the response “much lower than average”, they also have the highest numbers of respondents who regard their understanding to be “much higher than average”. Respondents from urban and suburban communities are more likely to consider their own understanding of energy issues to be below average.

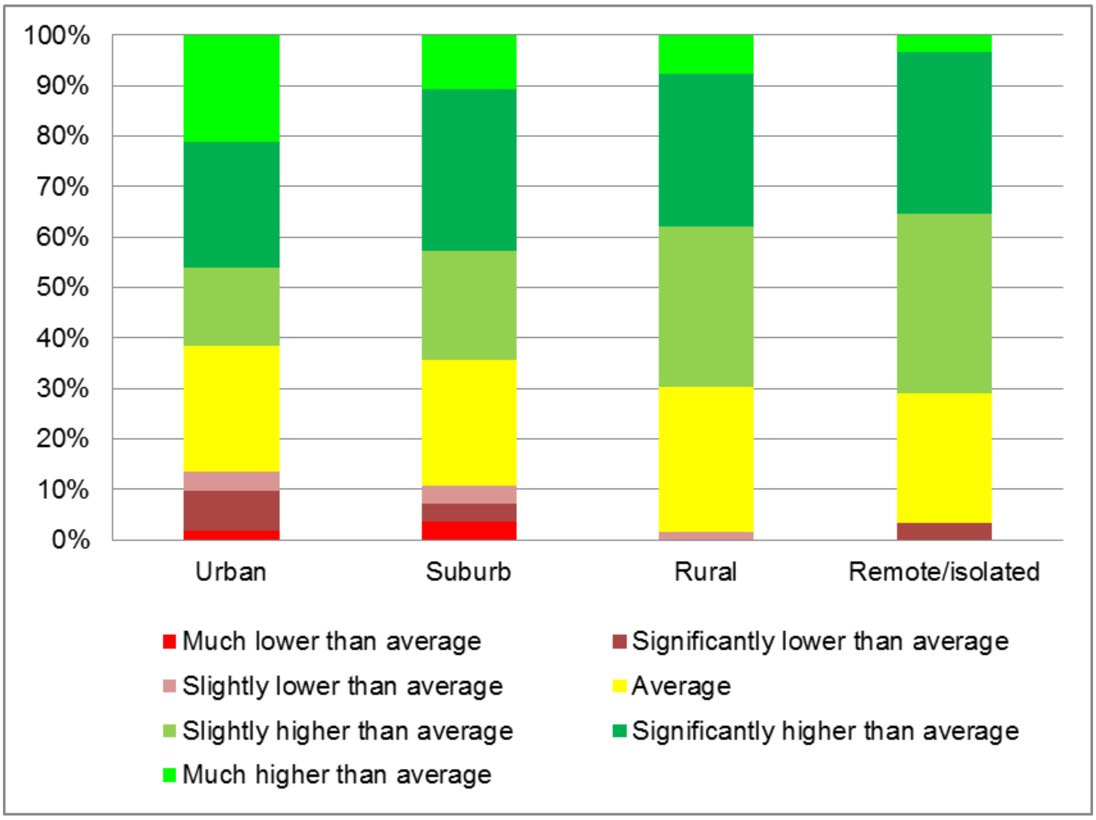


Figure 5-5 - Self-evaluation of knowledge and understanding of energy issues.

Respondents were asked to evaluate their household's energy consumption, again relative to an unspecified average. Over half of all respondents reported their own household consumption to be below average, indicating that they regard their energy consumption behaviour as being better than others. The fact that over 90% of respondents in urban communities estimated their consumption as being average or below average suggests that this phenomenon is more prevalent in urban communities. The results are shown in Figure 5-6.

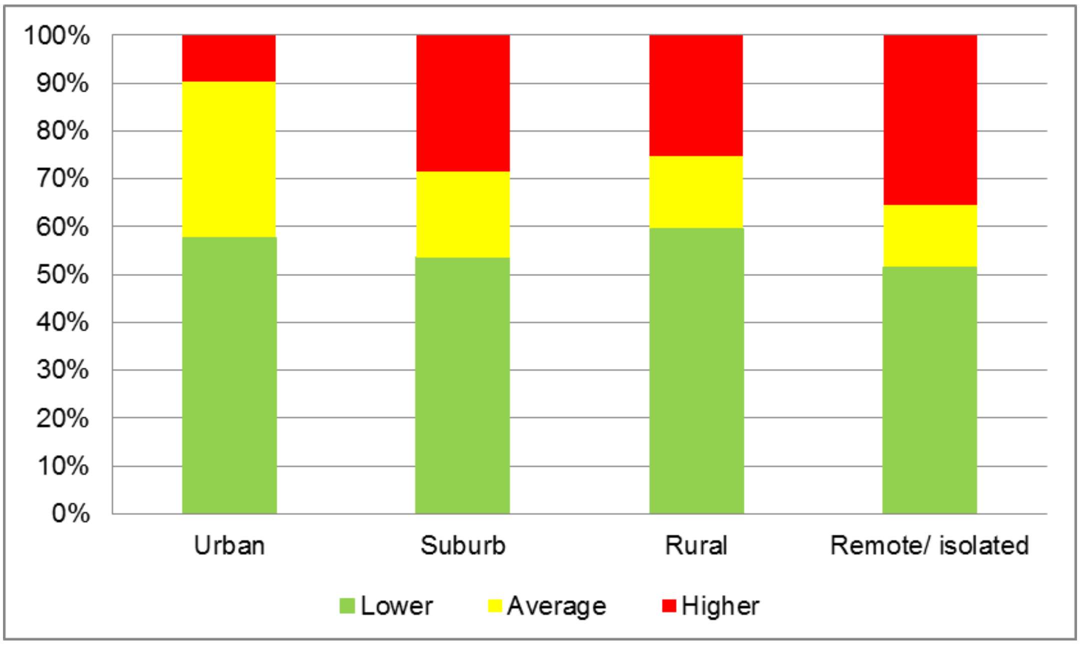


Figure 5-6 - Self-evaluation of household consumption relative to 'typical' household of similar size.

5.3.3 Attitudes towards Demand Response

This section of the survey addressed the comparatively more complex issue of DR. In order to gauge attitudes towards DR in a consistent manner and to ensure a rudimentary level of understanding, respondents were provided with a brief summary of what DR involves:

> *"Demand response is a term used to describe adjustments made to energy consumption, by altering either the timing or the amount of consumption. These adjustments would typically be made in response to changes in the price of energy, and would occur either as a result of voluntary consumer action, or via automated control technology. For example, a price increase during a certain time of day could lead to consumers reducing their demand during that time, or waiting until later to consume energy."*

Respondents were initially asked if they would be willing to alter their energy consumption in the way described. The results showed a consistent level of willingness across all community types, with a combined average of 80.6% of respondents reporting willingness to alter their consumption as described.

The results show negligible locational variation in the proportion of respondents who would be willing to alter their energy consumption, with ‘Urban’ and ‘Remote or isolated’ communities having the highest levels of willingness (84%) and ‘Rural’ having the lowest (77%). This suggests that community type is not a key factor in determining consumer receptiveness towards DR. This result suggests that receptiveness is more likely to be a result of cultural and socio-economic factors rather than location. Nevertheless, it was anticipated that respondents in remote/isolated areas (who consider their energy consumption more frequently and who regard energy issues as a high priority) might exhibit an above-average level of willingness to adopt DR.

It should also be noted that self-reporting may have resulted in an artificially high number of willing responses. This is discussed in more detail later in this chapter.

Respondents were asked if they would consider using (cost-effective) technology to automatically adapt their energy consumption pattern. In total, 62% reported that they would use said technology “even if some restrictions were required”, with 5% willing to adopt the use of technology “no matter what restrictions were required”. Whilst no specific restrictions were specified, this shows the generally receptive attitude towards technology use, with two thirds of respondents willing to accept some form of restrictions. These results echo the findings of Mah et al., 2012, who found consumers to be receptive to the use of micro-grid technologies to help them play a more active role in energy decision making.

As shown in Figure 5-7, 31% of respondents would only be willing to accept such technology if its effect was “undetectable during everyday use”.

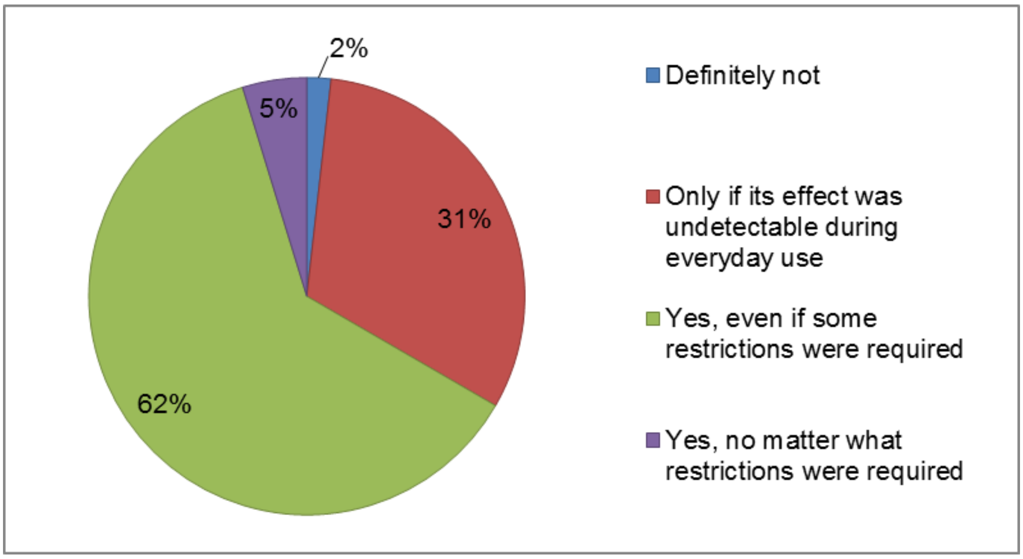


Figure 5-7 - Breakdown of respondent willingness to use technology to alter Energy Consumption.

Only 1.8% of respondents reported that they would "Definitely not" consider using cost-effective technology to alter their energy consumption. The reasons specified include fears about fire safety that might result from loads being shifted to night time, and general concerns about inconvenience. One respondent also reported that the altering of consumption behaviour would be "too much like Big Brother" - a view that represents the challenges associated with ensuring DR does not appear to be overly invasive or disruptive to consumers, or primarily for the benefit of external parties i.e. system/network operators. Such a perception is likely to further contribute to the lack of trust currently placed in the energy industry by consumers (Strong & Which?, 2014).

Respondents who reported that they would be willing to alter their energy consumption were then asked to rank the following motivating factors in order of importance:

1. Achieving (minor) financial savings;
2. Reducing their environmental impact;
3. Contributing to the efficient operation of the wider energy supply system;

4. Other (respondents were asked to specify other factors).

The most popular primary motivation was financial, with 44% of responses, followed by environmental with 32% and social with 24%. The most common ranking was the same as that shown above (i.e. with the four factors above being listed in the order ‘1-2-3-4’), with 34% of respondents choosing to leave the list as it appeared. This can be seen as the “financially motivated” option, with financial savings given the highest priority. The next most common order (chosen by 26% of respondents) was ‘2-1-3-4’ or the “environmentally motivated” option. This was followed by ‘3-1-2-4’, which was selected by 19% of respondents. This places the overall operation of the wider energy system as the top priority and can therefore be referred to as the “socially motivated” or “altruistic” option. These three configurations account for 79% of all responses.

This hierarchy of motivations is also observable when we examine the motivations listed second in the list of priorities, with 47% of second priority votes going to financial gain, 42% going to reducing environmental impact and 11% for contribution towards efficient system operation. The status of this social motivation as the third priority motivating factor is cemented by the fact that 57% of respondents listed it third in their list of priorities, more than twice the number of the next placed factor (reduction environmental impact, with 27%).

Few additional factors were suggested by respondents, with 98% ranking the “Other” option lowest, and choosing to leave it blank. Those who did specify additional motivations cited the desire to set an example in their community, the abundance of locally available fuel, and a range of other social and environmental motivations, including the desire to lessen the UK’s reliance on foreign fuel imports.

There is also some variation in responses according to community type, with 46% of respondents from urban and suburban communities reporting financial gain as their primary motivation, compared to 42% of respondents from rural and remote or isolated communities. Urban and suburban respondents were also marginally less likely to give priority to social motivation than those in more rural communities (23% compared to 25% in rural and remote and isolated communities).

5.4 Discussion

The survey results provide a valuable insight into the attitudes that exist towards domestic demand flexibility and DR, and the use of enabling technology.

5.4.1 Attitudes towards demand response

The results appear to support the view that energy consumers in rural and remote or isolated communities have a greater knowledge and understanding of energy issues than those living in more urbanised areas. Whilst the reasons for this have not been fully explored in this study, it can likely be attributed to the fact that remote and rural communities are worst served by the prevailing centralised energy model, and as such are more likely to experience higher energy prices and poorer security of supply than those in more centralised areas, both of which combine to ensure that energy issues represent a higher priority for these communities.

The results also appear to validate the use of price-based DR schemes, with financial gain being the most common primary motivating factor among consumers who reported their willingness to adopt DR. Reporting of primary motivations for adopting DR practices were found to vary across the community types listed, with rural and remote and isolated communities being found to be marginally more likely to be socially motivated, and less likely to be financially motivated than those in urban and suburban communities. It should be noted, however, that the effectiveness of using purely financial incentives to promote behavioural change has been questioned by Jackson and Surrey, 2005 among others, and that financial incentives alone are likely to play only a part in achieving more widespread changes to the way energy is consumed in SAHES and other areas of society. Indeed, the prevalence of other motivating factors, such as the desire to reduce environmental impact and the desire to contribute to smooth system operation for the community, show that more altruistic motivations do exist, and could therefore have a role to play also.

As previous chapters have discussed, one potentially less onerous and complex alternative to behavioural change is the use of technology to automate consumer interaction with their energy system. With a high degree of receptiveness towards the use of cost-effective technology exhibited by the results of this study, and the increasing capability of both metering and home automation technology, this is regarded as an area of significant potential.

The lack of variation in responses across the various community locations suggests that this is not a key factor in determining consumer receptiveness towards DR. The results indicate that a large majority of respondents were willing to adopt DR practices. Whilst the figure of 80% was higher than anticipated, the result echoes the findings of previous surveys, such as that conducted by (Mansouri, Newborough, & Probert, 1996). The high level of consumer willingness to adopt DR is also reflected by the fact that two thirds of respondents suggested that they would be willing to accept at least some of the restrictions that may be associated with the use of technology to aid the altering of demand. This surprising result appears to contradict the idea that consumers are likely to be resistant to any use of technology that could be regarded as allowing “Big Brother” to dictate their energy consumption habits (though this opinion was expressed by some respondents). However, it should be noted that the number of willing consumers may well be lower in practice, given that the survey presented in this chapter involved self-reporting only. Conversely however, it is also worth noting that respondents were not provided with details of how DR might be implemented, so the reality may be less invasive or onerous than the perception of some respondents.

5.4.2 The role of energy pricing

The role of energy pricing within the context of these results presents an interesting and challenging contradiction. While respondents demonstrated their widespread support for DR and the use of technology to implement it (albeit merely in principle) they also showed - and in some cases deliberately voiced - their confusion and lack of understanding when it comes to energy tariffs. This result is interesting within the context of recent calls to simplify energy billing and reduce the number of tariffs available to consumers, such as that from the UK energy regulator Ofgem (Ofgem, 2014). This illustrates the challenges associated with introducing additional complexity to energy metering and billing in a way that is easily understood by consumers.

Furthermore, the current lack of trust exhibited towards energy companies is likely to make this task all the more difficult. However, such attitudes are considered far less likely to prevail in community owned and operated systems.

5.4.3 Potential limitations of findings

As with any survey methodology, it is important to recognise the associated limitations which can be placed on the accuracy and applicability of the resulting findings.

The nature of the chain-referral sampling method used does not guarantee a high degree of representativeness, and affords little control over the sample size and distribution, which can potentially give rise to sampling bias. As a result, the results and outcomes from the survey cannot necessarily be seen as being wholly representative of either the communities where respondents took part, or the general UK (or Scottish) population as a whole. They do, however, provide a useful insight into how attitudes towards energy consumption differ according to community location.

Another relevant factor to consider is the risk that the web-based format of the survey excluded consumers with little or no internet access or computer literacy. Internet access in remote and isolated communities in particular has itself been the subject of much publicity and investment in the UK in recent years (Tookey, Whalley, & Howick, 2006). For the purposes of this study, the benefits of utilising social media and email referral were found to outweigh these limitations.

As alluded to previously, the use of self-reporting also has associated limitations, stemming from the potential inconsistency between respondents' stated views and their actual behaviour. This effect may have contributed towards the unexpectedly high number of consumers who indicated that they would be willing to consider the use of technology (and subsequent restrictions) to help alter their demand. However, this effect may also mask the true importance of financial gain as a motivating factor for those willing to alter their energy consumption, due to the possibility that self-reporting has resulted in respondents exhibiting more altruistic attitudes than perhaps would be the case in reality. Therefore, the possibility that financial savings could play an even more significant role in motivating consumers than the results suggest should be seriously considered.

5.5 Conclusions

The survey presented in this chapter was intended to supplement the existing literature in the field of domestic energy consumption and domestic DR, in order to provide some further investigation into the viability of using financial incentives (in the form of variable energy pricing) to elicit DR, and the use of technology to facilitate it. In addition, the survey aimed to compare attitudes towards DR and energy consumption behaviour in general which exist in remote and isolated communities with those of consumers from more urban areas. Such a survey - comparing attitudes towards energy consumption behaviour - represents a novel contribution to the field, and provides a useful insight into how attitudes can vary with location.

While a study of this scale cannot claim to be fully representative, the results nevertheless provide an informative insight into the energy consumption attitudes of domestic consumers. In order to ensure a sufficient distribution of respondents when it came to urban, rural and remote locations, the chain-referral sampling method was found to facilitate a partially targeted approach which provided access to existing social networks.

The findings suggest not only that consumers are willing to engage in DR, but also that financial incentivisation is the most effective source of motivation for doing so. This appears to support the use of variable energy pricing to elicit DR among domestic consumers. The results of the survey also show that attitudes towards the adoption of DR techniques does not vary significantly with location, with those in remote and isolated communities showing just as much willingness to adopt DR as those in more urban areas. Lastly (and crucially), the results also indicate a high degree of receptiveness towards the use of cost-effective technology to help facilitate DR in the home. Just how such technology could be implemented in a cost-effective way is outwith the scope of this study, but this result nevertheless supports the view that technology has a key role to play in domestic energy consumption and in the facilitation of DR.

The next chapter describes the development of a SAHES model which will later be used to simulate the application of financial incentives (in the form of variable energy pricing strategies) in order to promote DR.

5.6 References for Chapter 5

Biernacki, P., & Waldorf, D. (1981). Snowball sampling: Problems and techniques of chain referral sampling. *Sociological Methods & Research*, *10*(2), 141–163.

Druckman, A., & Jackson, T. (2008). Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy*, *36*(8), 3177–3192. doi:10.1016/j.enpol.2008.03.021

DTAS. (2014). Development Trusts Association Scotland. *Directory of Members*. Retrieved from http://www.dtascot.org.uk/content/directory-of-members

Jackson, T., & Surrey, G. (2005). Motivating Sustainable Consumption: a review of evidence on consumer behaviour and behavioural change. *A Report to the Sustainable Development Research Network*. Retrieved from https://www.c2p2online.com/documents/MotivatingSC.pdf

Mah, D. N., van der Vleuten, J. M., Hills, P., & Tao, J. (2012). Consumer perceptions of smart grid development: Results of a Hong Kong survey and policy implications. *Energy Policy*, *49*, 204–216. doi:10.1016/j.enpol.2012.05.055

Mansouri, I., Newborough, M., & Probert, D. (1996). Energy consumption in UK households: impact of domestic electrical appliances. *Applied Energy*, *54*(3), 211–285.

Ofgem. (2014). Ofgem Simplification Plan 2014-15. Ofgem, UK. Retrieved from https://www.ofgem.gov.uk/ofgem-publications/88528/simplificationplan2014-15.pdf

Qualtrics. (2014). Qualtrics. Provo, Utah, USA.: Qualtrics. Retrieved from http://www.qualtrics.com/

Strong, L., & Which? (2014). Wrestling with trust. In *Energy Systems Conference 2014*.

Tookey, A., Whalley, J., & Howick, S. (2006). Broadband diffusion in remote and rural Scotland. *Telecommunications Policy*, *30*(8-9), 481–495. doi:10.1016/j.telpol.2006.06.001

Which? (2014). Energy Tariffs Explained. *www.which.co.uk*. Retrieved from http://www.which.co.uk/switch/energy-advice/energy-tariffs-explained

Chapter 6: The Modelling of Stand-Alone Hybrid Energy Systems

6.1 Modelling Aims and Objectives

This chapter describes the design, development and verification/validation of a notional Stand Alone Hybrid Energy System (SAHES) model which will later be used to simulate the DR of residential consumers under variable energy pricing conditions. The objectives of the modelling process are therefore as follows:

1. to define a series of electrical demand profiles which can be deemed to be representative of a notional SAHES, using existing tools
2. to develop a hybrid energy system specification capable of meeting the associated energy demand
3. to develop an algorithm which is representative of financially driven residential consumer demand response within SAHES

4. to adapt existing variable energy pricing strategies such that they can be applied to the developed SAHES model

This chapter focuses on the modelling process, which aims to satisfy these objectives. It also sets out the scenarios and conditions which will serve as the model input data during the experimentation phase, the results of which are presented in Chapter 7.

6.1.1 Modelling methodology

The main challenge associated with the development of the model stems from the need for it to be sufficiently accurate and detailed so as to provide meaningful results, whilst simultaneously ensuring that such a level of detail does not limit the applicability and transferability of the results. This is particularly pertinent given the range of scale and diversity associated with existing SAHES, and the often highly site-specific nature of such projects.

The modelling process used was based on that outlined by Sargent (Sargent 1981; Sargent 2005). This method provides a rigorous approach to the validation and verification of computer models which simulate real or proposed problem entities, thus maximising the suitability of a model for its chosen application. A simplified version of the development process is shown below in Figure 6-1:

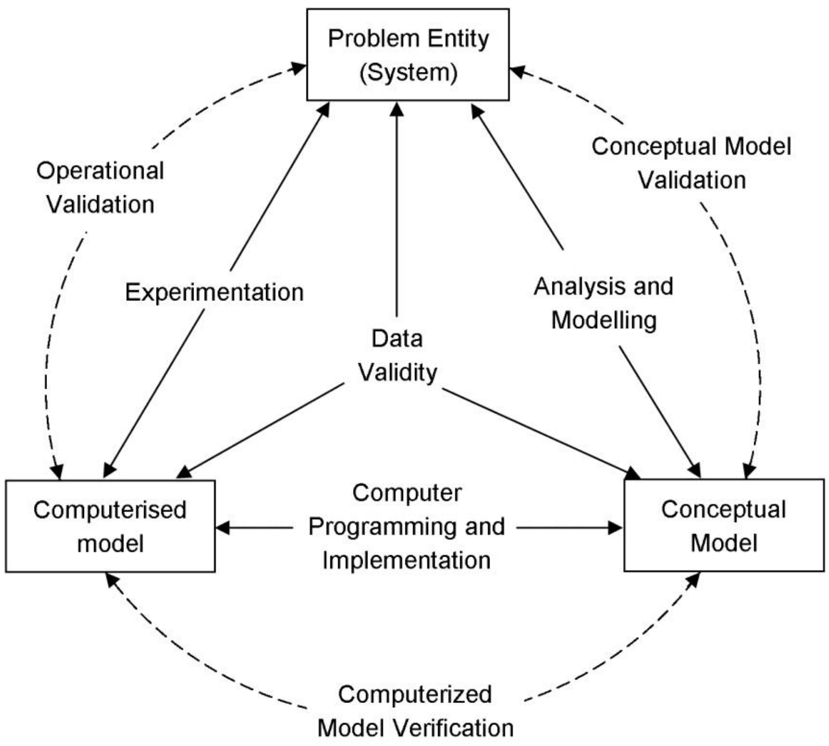


Figure 6-1 - Sargent's computerised model development process (Sargent 1981).

As can be seen above, the method is centred on three main models/systems. The first of these is the **problem entity** itself - that is, the real or proposed system being modelled. Having identified the objectives of the modelling process, knowledge of the problem entity can be used to develop a **conceptual model**. This involves the development of a logical/mathematical representation of the problem entity, relative to the specified modelling objectives. The conceptual model is validated by ensuring that any theories and assumptions it makes can be deemed sufficiently accurate/ reasonable for the given modelling objectives.

The next stage in the modelling process involves implementing the conceptual model using computer programming techniques, a process which results in a **computerised model** which can then be used to conduct the relevant experimentation. The final model is then validated by ensuring that the programming and implementation is correct i.e. that the accuracy of the conceptual model is not lost/diminished by the implementation process. The experimentation phase can then take place, and inferences about the problem entity drawn. This phase is also subject to validation in order to ensure that the model's output is of sufficient detail and accuracy for the intended application.

The use of Sargent's framework helps to ensure that the notional SAHES model which is developed is capable of producing useful results. The four key stages of the design and development process reflect the objectives set out above, and focus on the four main capabilities that are required of the SAHES model, as described previously.

6.2 Demand Profiling

This first step of the process involves characterising and compiling the various energy consumption patterns of the consumers featured in the model, in order to form the basis of the overall energy demand profile associated with the notional SAHES being modelled. These energy demand profiles will also later serve as the basis for the specification of energy generation and storage components which comprise the SAHES.

6.2.1 A high-resolution domestic energy demand model

The demand profiling process must be capable of generating a sufficiently detailed demand profile which reflects the likely energy consumption behaviour and characteristics of residential consumers in SAHES. Given that the model is to be used to simulate consumer response to variable energy pricing, it follows that energy consumption should be of a sufficiently high resolution, both temporally and elementally i.e. with each household's energy demand being disaggregated to an appliance level, and over an appropriate timestep period. This in turn enables individual loads to be shifted, curtailed or grown in response to energy price conditions. There are a number of methods and tools which have the capability to compile domestic demand profiles (Torriti 2014). In particular, recent years have seen the emergence of bottom-up, Markov-based, occupancy driven approaches. These approaches to domestic demand profiling allow modellers to create high temporal resolution models of domestic consumption based on predicted patterns of occupant activity, and are therefore regarded as the best currently available (Grandjean et al. 2012; Swan & Ugursal 2009). The level of detail provided by this approach also allows demand to be disaggregated to the appliance level - a requirement of this project given the need to vary specific appliance loads on an individual basis. This requirement effectively rules out a top-down approach.

Wilke (Wilke 2013) does propose a bottom-up approach to domestic demand profiling which does not use a Markov-based approach, but this has been found to be less accurate than Markov-based alternatives (Flett & Kelly 2014).

Flett and Kelly (Flett & Kelly 2015) identify two key variants of the bottom-up, Markov-based approach, developed by Richardson et al. (Richardson et al. 2010; Richardson et al. 2008) and Widén and Wackelgard (Widén & Wäckelgård 2010). Both models utilise a first order Markov-based approach, are occupancy driven and utilise Time Use Survey data as a basis for appliance consumption profiles. The main difference between the two stems from the way in which household occupancy is viewed. While the Richardson model uses an approach based on total household size i.e. the number of permanent occupants living in the household, the Widén and Wackelgard model treats each individual occupant independently regardless of household size. This results in group activity being unrepresented, and is therefore seen as providing a less accurate representation of the way in which households consume energy. This approach also increases the data requirements significantly.

The Richardson model was therefore selected as the most appropriate for this project. The architecture of the model is shown in Figure 6-2.

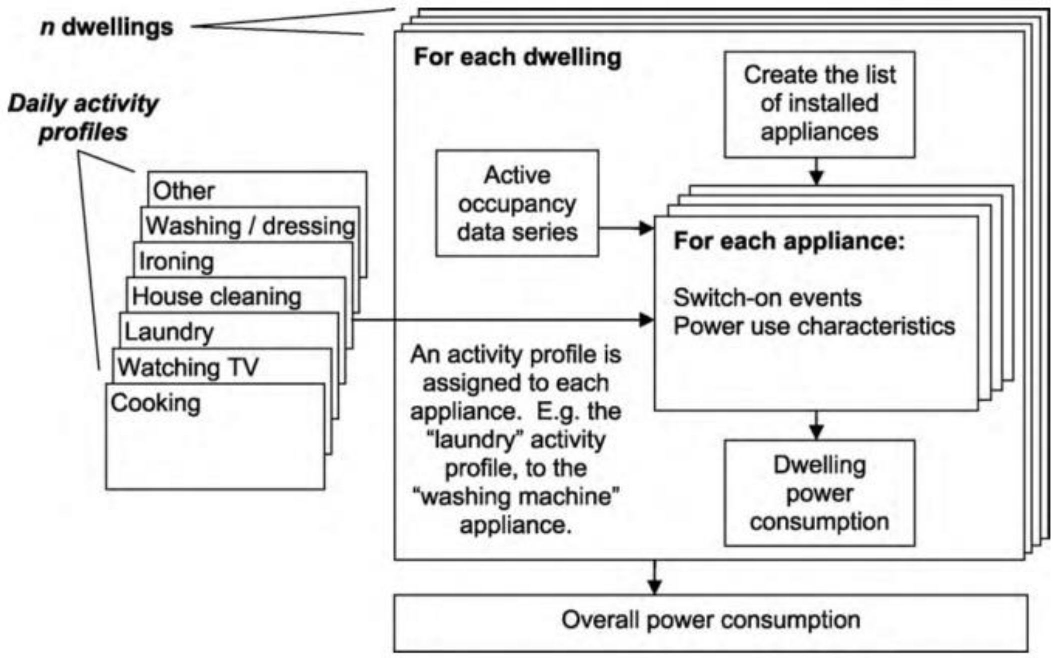


Figure 6-2 - The architecture of the Richardson domestic electricity demand model (from (Richardson et al. 2010)).

The model uses a number of daily activity profiles, which reflect the probability of a given activity occurring throughout the day. These are based on Time Use Survey data, and are the same for all dwellings.

At the individual dwelling level, the electrical demand of each household is a function of active occupancy and appliance ownership. The former takes into account the number of permanent occupants in the dwelling, which can be pre-defined by the user (see section 6.2.4). The latter can be assigned on a pseudo-random basis by the model, but for the purposes of this project have are also pre-defined (see section 6.2.5). Each appliance is linked to an activity profile e.g. the use of an iron is linked to the "ironing" activity profile.

This information is used in combination to determine if/when each appliance present within the dwelling in question is operational throughout the day, resulting in a daily electrical consumption profile for each active appliance. The daily household electrical consumption is therefore calculated as the sum of all the active appliance consumption totals.

6.2.2 Profile period selection

In order to ensure that all climatic (and therefore energy generation and demand) extremes were accounted for, whilst at the same time limiting the volume of associated data where possible, it was decided that focusing on four seasonal weekdays i.e. one day for each season, would give a good representation of a notional annual data set, and the variation which would occur within it.

It should be noted at this stage that the Richardson model fails to fully account for the seasonal variation in demand which arises from people staying indoors more during the colder months of the year. It does however account for temperature variations, and the resulting impact upon the demand for space and water heating, as well as the increased demand for artificial lighting during the winter months when daylight hours are reduced.

6.2.3 Community characteristics

In order to arrive at a community energy demand profile which can be used to size and specify an energy system, it is necessary to first define the size and characteristics of the notional community being modelled.

The SAHES model includes the demand from a total of one hundred households. This number was chosen for a number of reasons (besides ease of calculation). A one hundred household community was deemed likely to be of a sufficient size as to require a clearly defined, community-wide energy pricing strategy. It was also deemed to be the minimum size at which the required community organisation infrastructure required to administer such a strategy was likely to exist. Unlike a much smaller community, such a community would also have a broad range of potentially viable renewable and conventional generation sources to choose from.

This is reflected in existing SAHES, such as the Scottish islands of Eigg and Fair Isle, and the remote community of Applecross.

6.2.4 Household occupancy

In an attempt to best reflect the context, household occupancy rates were based on the responses to the consumer survey presented in Chapter 5 which came from those in rural and remote/isolated communities. These values were then compared against UK averages, as reported by the Office for National Statistics (Office for National Statistics 2013). The results of this comparison can be seen in Table 6-1.

Table 6-1 - Comparison of survey household occupancy results with 2011 UK census data.

Number of permanent residents	Survey data (% of total)	2011 UK Census Data (% of total)
1 person	15	30.5
2 people	52	34
3 people	16	15.5
4 people	14	13
5+ people	3	7

As is clear from the above table, the survey data differs from the UK census data most notably in low occupancy households, with the number of single occupancy households being around half the UK-wide value, and the number of households with two occupants being considerably higher (52% compared to 34%). The survey data also features fewer households with five or more occupants than the census data. This shows that the survey data reflects the fact that rural areas have a lower proportion of single-occupancy households than urban areas (Gower 2013) and otherwise reflects UK-wide data regarding household size. The data from the survey was therefore deemed suitable for use within the SAHES model.

In addition to variation in the number of permanent residents, the primary contributing factor behind the variation in the demand profiles of otherwise similar households is their occupancy patterns. The Richardson model includes an occupancy profile generating capability, based on the approach previously presented by the authors of the tool, which is itself based on data from the Time of Use Survey, conducted in the UK in 2000 (Office for National Statistics 2003). The occupancy model is based on the concept of "active occupancy". This refers to the number of occupants who are active i.e. awake, within a household at any one time, and as such it varies throughout the day in a pseudo stochastic nature that is intended to mimic the natural behaviour of residents. It should be noted that the model does not account for any differences in active occupancy patterns which may occur in SAHES, such as the increased likelihood of home-based business and working patterns (Yohanis et al. 2008).

6.2.5 Appliance use

As discussed in section 6.2.1, appliance ownership and use is central to the Richardson model. At the individual dwelling level, the list of installed appliances is typically assigned on a pseudo-random basis by the model, based on national statistical appliance ownership data from DECC (DECC 2014). However, in order to enable a direct comparison of DR rates between different levels of appliance usage, three appliance ownership schedules have been defined for use in this project.

Appliance ownership levels within these groups are an approximation of the results of the Energy Follow-Up Survey conducted in 2011 by the Building Research Establishment (BRE), which provides UK statistics relating to ownership of domestic appliances and cooking equipment (DECC & BRE 2014). They range from a 'Low' level of ownership (single television, no secondary freezer, no microwave or additional small cooking appliances) to a 'High' level which incorporates the vast majority of domestic appliances, including three televisions, small cooking appliances, multiple laundry appliances, increased IT appliance ownership etc. The breakdown of these groups is shown in Table 6-2.

Table 6-2 - Breakdown of appliance ownership according to usage banding.

	Appliance Usage Group		
	LOW	MED	HIGH
Chest freezer	✕	✓	✓
Fridge freezer	✓	✓	✓
Answer machine	✕	✓	✓
Cassette / CD Player	✕	✓	✓
Clock	✓	✓	✓
Cordless telephone	✓	✓	✓
Hi-Fi	✕	✓	✓
Iron	✓	✓	✓
Vacuum	✓	✓	✓
Fax	✕	✕	✓
Personal computer	✕	✓	✓
Printer	✕	✓	✓
TV 1	✓	✓	✓
TV 2	✕	✓	✓
TV 3	✕	✕	✓
VCR / DVD	✓	✓	✓
TV Receiver box	✓	✓	✓
Hob	✓	✓	✓
Oven	✓	✓	✓
Microwave	✕	✓	✓
Kettle	✓	✓	✓
Small cooking (group)	✕	✕	✓
Dish washer	✕	✓	✓
Tumble dryer	✕	✕	✓
Washing machine	✕	✕	✓
Washer dryer	✓	✓	✕
Electric shower	✓	✓	✓
Lighting	✓	✓	✓

The one hundred households were split evenly into these groups, with both 'Low' and 'High' ownership groups each having 33 households and the 'Medium' group 34. This distribution ensured that the ownership rates throughout the community as a whole reflected the ownership statistics published in the Energy Follow-Up Survey.

Another key distinguishing factor which determines the demand profile of a household is the presence of electric space or water heating appliances, such as electric element space heaters and water immersion heaters. Meeting the demand for space and water heating using electricity can lead to a significant increase in household electrical demand, given the demand for both in temperate maritime climates such as that of the UK. This is exemplified by the findings of Intertek (published by the Department for Energy & Climate Change), who found that of the 250 households surveyed, primary electric heating accounted for 64% of energy demand in the households where it was used. The use of *additional* electric space heating (the use of electric space heaters in homes with non-electric primary space heating systems) accounted for 23% (Intertek 2012). This high electrical demand is also apparent in the Richardson model, suggesting that the storage heater consumption characteristics featured in the model do not represent state-of-the-art storage heaters currently being deployed in projects such as NINES (Clarke et al. 2013). Therefore, given the scale of the additional electrical demand that would result from their widespread use, and despite their considerable potential for increasing flexible demand, it was decided that the use of the storage heaters as defined in the Richardson model would be unlikely to be deemed cost-effective in SAHES. Similarly, the use of heat pumps may also provide scope for additional flexibility (Arteconi et al. 2013) but are not featured within the Richardson model.

The use of electric heating in the model was therefore restricted to conventional electric space heating and instantaneous water heating. It should be noted that in both instances, electricity will be the primary source of heating, which should not be confused with the use of plug-in supplementary electric space heating or back-up immersion heating devices.

6.2.6 Household demand elasticity

In addition to the creation of three appliance usage groups, the one hundred households featured in the SAHES demand model were also assigned a level of demand elasticity. The households within these three groupings were assigned a set of elasticity values which set the limits to which each household can alter its consumption in response to changing energy prices (using the CPED equation discussed in Chapter 4). This not only introduces additional diversity between households, but also allows the likely variation in attitudes towards demand flexibility to be represented.

A total of three bandings were established to represent low, medium and high levels of demand elasticity, with each banding assigned a specific value for elasticity of substitution (applicable in the case of load shifting) and elasticity of demand (applicable in the case of load curtailment or growth). As with the aforementioned appliance usage bandings, these were assigned evenly across all 100 households i.e. 33 households with low and high elasticity bandings, and 34 with medium.

Within each banding, a further level of stratification of elasticity values was introduced in order to reflect the likelihood that consumers will opt to alter the use of some appliances more readily than others. This reflects the likely variation in the level of perceived disruption which is caused by altering the consumption associated with various appliances e.g. the disruption caused by shifting the use of a dishwasher is likely to be far less than the disruption caused by curtailing the use of space heating, so the former is therefore allocated a greater demand elasticity of substitution.

The values used for each elasticity group were based on historical and theoretical findings in relevant literature, as discussed in Chapter 4. They also reflect the likelihood that in-house technology such as direct/automated load control and sophisticated smart metering would be utilised to enable DR to be enacted in a way which reduces the associated transaction costs which exist for consumers. It is thought that such technology would also be required in order to implement the variable pricing strategies which will later be applied to the model. As noted by Spees and Lave (2007):

> *"In the future, short-run price elasticity and elasticity of substitution will depend on the sophistication of enabling technology".* (Spees & Lave 2007)

The elasticity values used for each of the bandings are as shown in Table 6-3. Table 6-3 also shows how the elasticity values assigned to different load and appliance groups varies. Load shifting appliances are allocated an elasticity of substitution value, which indicates the elasticity associated with a temporal shifting an appliance load cycle e.g. from a peak to an off-peak pricing period. Loads which are either curtailable or growable are assigned self-price elasticity values, which reflect the impact of price variation on the quantity of consumption.

Table 6-3 - Price elasticity of demand values for each household elasticity banding.

	Household elasticity banding:		
	LOW	MED	HIGH
Shiftable appliance loads	0.15	0.2	0.25
Shiftable electric heating loads	1.125	1.5	1.875
Curtailable/growable loads - Low flexibility loads	±0.075	±0.1	±0.125
Curtailable/growable loads - Medium flexibility loads	±0.15	±0.2	±0.25
Curtailable/growable loads - High flexibility loads	±0.125	±0.25	±0.5

Curtailable/growable loads were divided into three subgroups - again to reflect the varying disruption/loss of utility that would arise from DR responses being enacted using different appliances, and the varying elasticity that would apply to each subgroup as a result. Across all three household elasticity bandings and load flexibility subgroups, elasticity values range from ±0.075 to ±0.5. This reflects the range of elasticity values present in the literature for recent variable pricing studies, as reviewed by Lijesen. While values of over ±0.5 have been reported in some instances, particularly by (Filippini 1995), these were attributed to partial and/or particularly intrusive DR schemes (Lijesen 2007). As such, the range of values selected was deemed to be appropriate. Since limited information is available when it comes to load growth in response to short-term price variations, the same values are used for load growth as for load curtailment.

For shiftable loads, a distinction was made between electric space heating loads and other shiftable appliances, given the evidence from literature which suggests that the load shifting of electric heating appliances can be implemented with minimal user disruption/loss of utility (Biviji et al. 2012; Lijesen 2007; Tracey & Wallach 2003). Other shiftable appliances were assigned a range of values which reflect the range of elasticity of substitution values present in literature, which were found by Tracey and Wallach to range from 0.12 to 0.37 in recent trial applications of ToU pricing.

6.2.7 Household classification

By classifying households based on their assigned elasticity and appliance use bandings, we create a total of nine main consumer types which are independent of household size. These are listed in Table 6-4.

Classifying the households in such a way enables the impact of variable pricing upon the consumption behaviour and the energy bills of each consumer type to be directly compared. This in turn will provide some indication of which consumer type(s) stand to benefit the most from the introduction of variable pricing, and similarly which consumer type(s) will stand to suffer the most disadvantages. Lastly, such a classification will also provide an indication of the extent to which the impact of variable pricing can vary from household to household.

Table 6-4 - Classification of household types.

Household Type	Demand Elasticity	Appliance Usage
1	Low	Low
2	Low	Med
3	Low	High
4	Med	Low
5	Med	Med
6	Med	High
7	High	Low
8	High	Med
9	High	High

6.2.8 Compilation of seasonal day demand profiles

Compiling a community-wide demand profile for each of the seasonal days requires collating all one hundred of the individual household demand profiles. These household profiles, an example of which is shown in Figure 6-3, exhibit the highly variable short-term peaks which characterise consumption at the individual household scale.

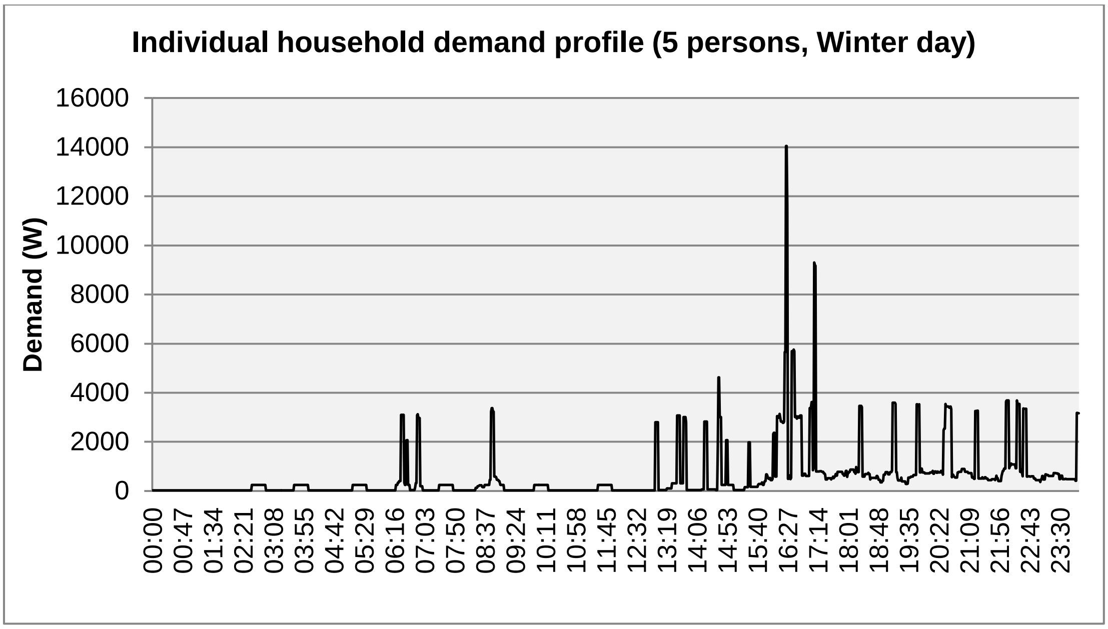


Figure 6-3 - Graph showing the minute-by-minute electrical consumption of a 5-person household over the course of a winter day.

When all 100 of the household profiles are added together, these short peaks in demand are largely evened out. The resulting community-wide demand profiles for all 4 of the seasonal days are shown in Figure 6-4.

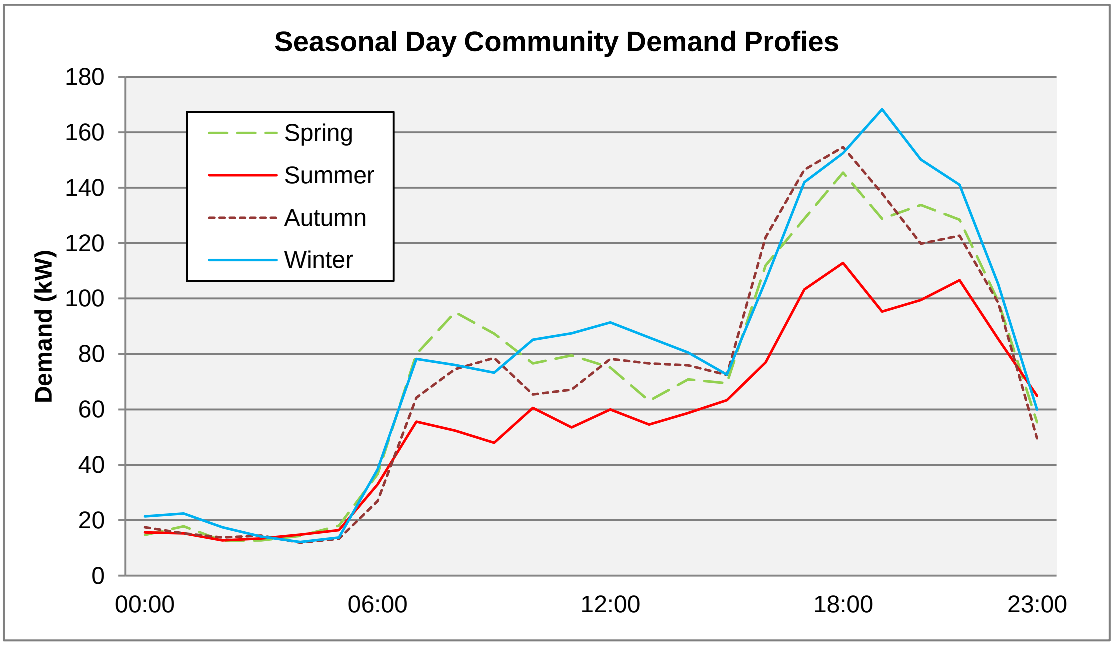


Figure 6-4 - Graph of community-wide demand profiles for each seasonal day.

As shown in above, demand peaks at 168kW during the winter day and is at its lowest (12kW) during the early hours of the morning, when there is little variation between seasons. As expected, demand is notably lower in summer with a peak demand of 113kW. The summer profile also exhibits a smaller daily demand variation (maximum demand minus minimum demand) of 100kW, with the maximum variation of 156kW occurring during winter. This likely stems from the increased use of electric space heating during colder periods and the increased need for artificial light. As is also clearly visible in Figure 6-4, the demand profiles all exhibit a clear peak period between 18:00 and 23:00 hours. They also share a similar period of minimum demand between 00:00 and 06:00.

These seasonal demand profiles can then be compared to that of the UK as a whole, which is provided by BRE (BRE 2008) and is shown in Figure 6-5.

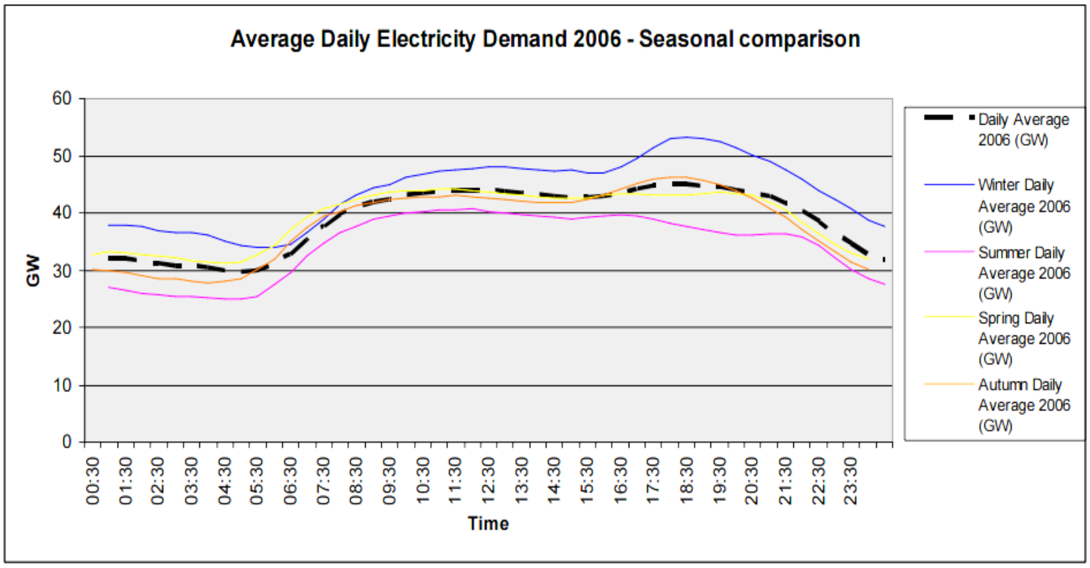


Figure 6-5 - Graph comparing UK electrical demand during seasonal days (Source: BRE (2008).

While this fails to provide an accurate means of verifying the profiles generated, it does exhibit the same basic characteristics i.e. the highest demand occurs during winter and the lowest in summer. Figure 6-5 also exhibits some evidence of the evening peak which is prominent in the generated community-wide profile. However, as the data includes the electrical demand from other sectors e.g.

commercial and industrial energy demand, the base level demand is far higher, leading to a less pronounced variation in demand between day time and night time hours.

The four seasonal daily profiles can also be used to calculate the average projected electrical consumption for each household, which can in turn be compared with national average figures in order to gauge the need for any further calibration of the demand profiling. This is achieved by calculating the average total consumption for the community across all four seasonal days, to give an average daily total. This can then be divided by the number of households to give an average daily household consumption figure, which can then be multiplied by 365 in order to give a projected annual mean household consumption.

This process results in an average household electrical demand of 6151kWh/year, which is notably higher than the UK average figure presented by DECC of 4170kWh/year (DECC 2014). The Richardson model itself has been shown to align with national averages (Richardson et al. 2010), and is therefore not the source of this increase. Instead, it can be attributed to the comparative prominence of electric space and water heating in the model, which reflects the ownership levels reported by consumers from remote and isolated communities in the consumer attitudes survey presented in the previous chapter. The resulting increase in average annual consumption is verified by the findings of the Energy Follow-Up Survey of 2011, which reported that the median annualised electricity consumption of households using electric heating systems (in the form of either storage heaters or individual room heaters) was 6700kWh (DECC & BRE 2014). With this in mind, the average annual electrical consumption resulting from the demand profiling process was deemed appropriate and in need of no further alterations or calibration.

6.3 Energy Supply Profiling

Having defined the energy demand characteristics of the SAHES being modelled, the second key aspect of the modelling process relates to the selection and sizing of an appropriate hybrid energy system which is capable of meeting the energy demands of the community in question. The selection process was designed to mirror that which would likely be used to size and specify SAHES in the real world, and as such included the following considerations:

- Local climatic conditions and resource appraisal
- The provision of back-up generation
- On-site energy storage
- High level cost analysis, allowing for the economic comparison of different technologies and configurations

6.3.1 Sizing SAHES using HOMER

There are a number of tools which can be used for the design and specification of SAHES (Mendes et al. 2011). While there are many tools available which are capable of modelling SAHES, the chosen tool must be capable of incorporating all of the considerations listed above, as well as being able to size the various system components in order to match the previously developed community demand profile.

As identified by Mendes et al, “HOMER” (developed by the American National Renewable Energy Laboratory (NREL)) uses a simulation-based approach which allows SAHES specification to undergo optimisation from both technical and economic perspectives (Mendes et al. 2011; Homer Energy 2012).

HOMER is an established and widely used software tool designed to aid in the design and comparison of hybrid energy systems. The tool features optimisation and sensitivity analysis algorithms which can be used asses the technical and economic feasibility of a wide range of technological and infrastructure options, and has been used in the design and appraisal of a number of SAHES projects in countries around the world (Al-Karaghouli & Kazmerski 2010; Hafez & Bhattacharya 2012; Prodromidis & Coutelieris 2012; Prodromidis & Coutelieris 2010; Bekele & Tadesse 2012; Dorji et al. 2012). These projects range from small scale, community electrification projects in remote and unindustrialised countries to highly sophisticated larger scale projects.

In order to determine the ‘optimum’ system configuration for a specified problem, each HOMER model requires the following information:

- Either/both electricity and thermal demand profiles (as discussed above).
- Project location (so appropriate weather data can be used).
- Fuel and electricity costs.
- Economic inputs such as expected system life span, interest rates, fixed and operating costs.
- Technical constraints such as minimum renewables fraction (the minimum proportion of energy produced by the system from renewable sources) and maximum annual capacity shortage (as a percentage of annual load).
- The energy generation and storage technologies to be considered, including all potential sizing options and their associated capital costs.

HOMER then simulates the hourly operation of each of the resulting possible configurations and ranks those which satisfy the specified constraints, according to their associated Net Present Costs (Farret & Simões 2006). By using Net Present Cost as the basis for the ranking of viable options, this ensures that all costs and revenues throughout the life of the project are accounted for. This, coupled with the ability to incorporate a series of technical and operational constraints, make HOMER ideal for the purposes of this project.

But whilst HOMER can be seen in many respects to be ideally suited to use in this application, there are limitations associated with its use that must be acknowledged. Primarily, these limitations stem from the fact that the high level of detail it is capable of producing can only be achieved through the use of input data which is itself highly detailed. This limits its suitability for drawing generic and widely transferrable results and conclusions - an issue which is compounded by the highly location and context specific nature of SAHES.

6.3.2 Energy generation and storage technology specification

Having identified HOMER as an appropriate tool with which to model the notional SAHES, the first task involved extrapolating the community-wide energy demand profiles for each of the four representative seasonal weekdays (as described above) to cover the whole of their respective seasons. In order to create sufficient diversity of demand within each season, a random day-to-day and timestep-to-timestep variability of 25% was applied. This added variability to the model whilst maintaining the approximate 'shape' of the original daily profiles. The addition of this effectively arbitrary variation to the demand profiles ensures that the supply profiles provided by the HOMER model reflected the likelihood that both demand - and as a result, supply - profiles would vary significantly from the daily profiles created to represent 'seasonal days'. The seasonal day profiles themselves can therefore be thought of as representing the average/most likely demand to occur across the whole of each season. It therefore follows that since each season is three months long, that some additional variation is added to the model in order to reflect the potential for these typical profiles to vary within a season.

The next step involves the specification of the various technologies available for selection. The renewable technologies chosen reflect the likely abundance of renewable energy resources in many existing SAHES: wind, photovoltaics and small scale hydro power. Whilst this list is by no means extensive, and neglects technologies such as fuel cells and wave/tidal generation which may become more widely used in future, it has been compiled to reflect the resources often found in existing SAHES, particularly in the UK (to which the energy demand profile data - and later the energy resource data - relates). Due to the likelihood of its inclusion in SAHES as a means of providing back up generation, diesel generation capacity was also included, as was energy storage provision in the form of batteries. The technologies selected for inclusion in the HOMER SAHES design optimization process were therefore as follows:

- Wind turbines (two turbines were available for selection, with rated power outputs of 10kW and 65kW, with between 2 and 7 turbines available for selection);
- Photovoltaic (PV) array (available for selection in 5kW increments, from 5kW to 100kW);
- Micro hydro (with a single rated output of 50kW);
- Diesel (back-up) generator (available in 20kW increments, from 100kW to 400kW);
- Energy storage (in the form of batteries, connected in strings of 16, with the number of strings available ranging from 12 to 30);
- Converter (DC to AC. Sizing was dependent on PV array and battery storage sizing).

It should be noted that only one sizing option was included in the analysis for hydro installations, in order to reflect the likelihood of the resource being constrained by local conditions.

6.3.3 Initial energy demand-supply match appraisal

Having generated both supply and demand profiles for each of the seasonal days, it was then possible to appraise the demand/supply matches that arose. The Renewable Energy Supply (RES) generation and demand plots which occur on the Spring seasonal day are shown in Figure 6-6 to Figure 6-8.

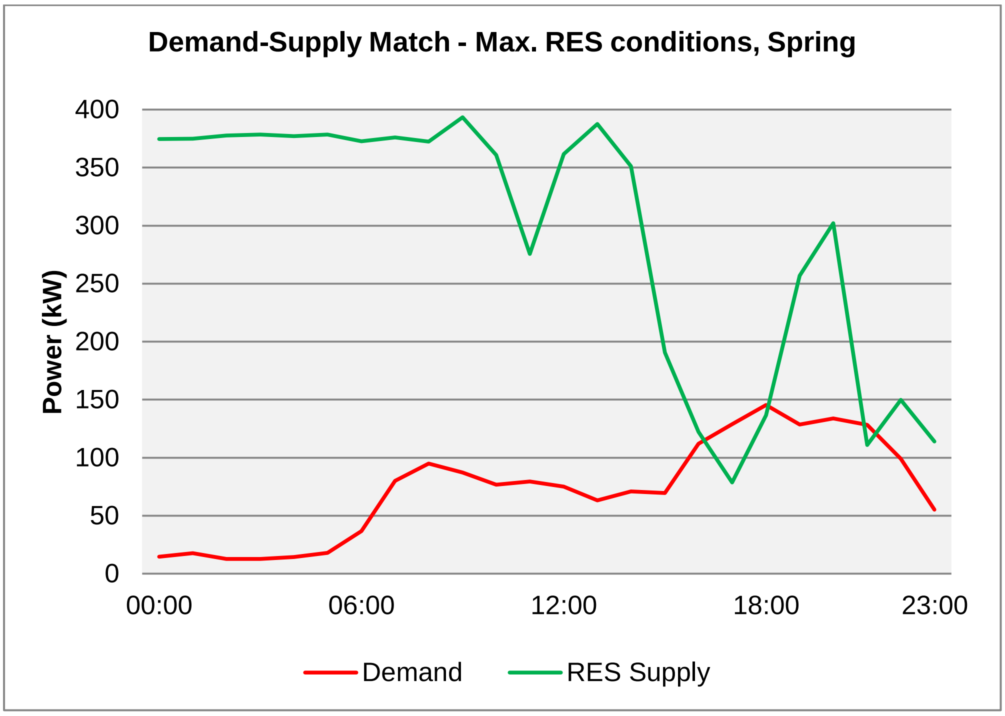


Figure 6-6 - Demand and RES supply profiles under maximum RES conditions during the Spring seasonal day.

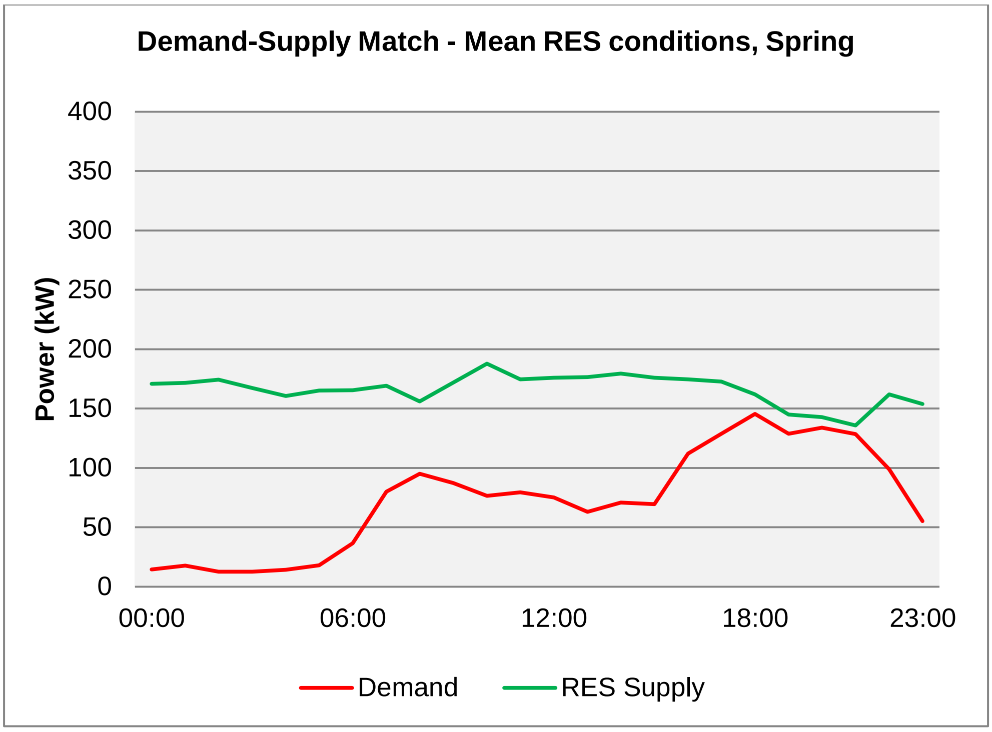


Figure 6-7 - Demand and RES supply profiles under mean RES conditions during the Spring seasonal day.

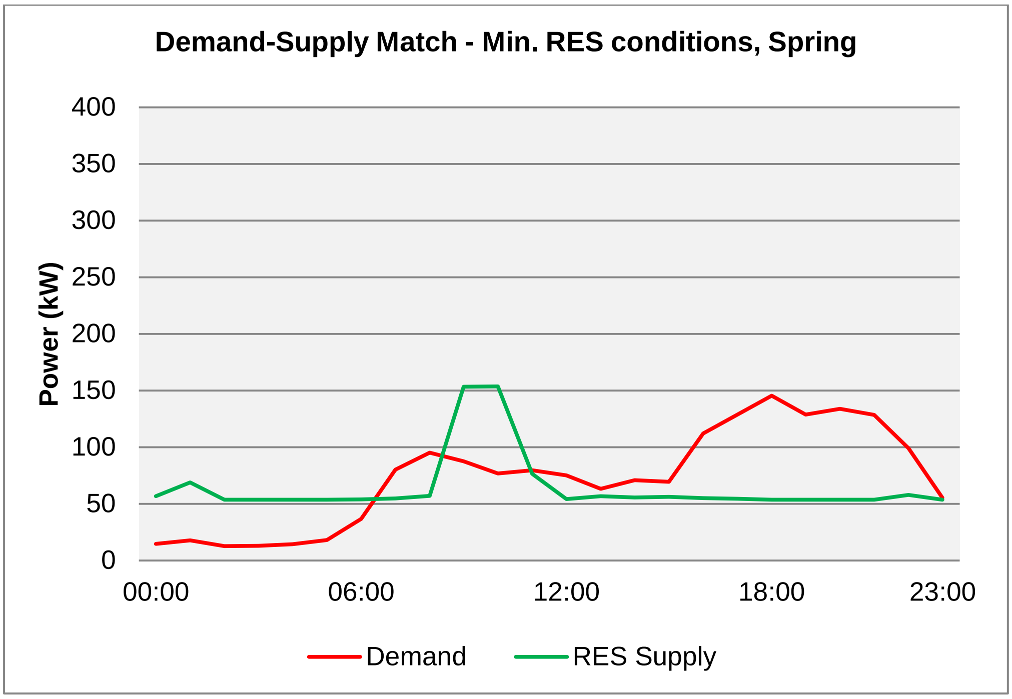


Figure 6-8 - Demand and RES supply profiles under minimum RES conditions during the Spring seasonal day.

As can be seen above, the specified combination of RES is capable of meeting (and in most instances surpassing) the overall levels of demand which could reasonably be expected during a typical Spring day. While there are times when demand exceeds RES, the provision of back-up supply in the form of diesel generation and energy storage in the form of batteries means that the SAHES components specified by HOMER are capable of meeting the energy demands of the notional community. The graphs above also highlight the level of surplus that can result from ensuring that this is the case, which also serves to illustrate one of the primary aims of DR in a context such as this: reducing the need to over-specify generation and on-site storage components.

Under mean RES conditions, demand does not exceed the supply from RES at any point. Under such circumstances, no diesel generation would be required, with surplus energy being stored (assuming the battery storage is not at full capacity). Under both maximum and minimum RES conditions, demand exceeds RES supply for between 4 and 6 hours in the evening. These periods of deficit would require a combination of back-up generation from the diesel generator and supply from the battery storage. These periods of deficit (and more specifically their reduction) will later be the focus of the price-based DR techniques, the development of which is described in the following section.

6.4 Pricing Strategy Development

The design of any energy tariff is a highly complex process, and is typically based on a multitude of data regarding market conditions, wholesale price forecasts, reserve levels, climate data, consumer research and many more socio-economic considerations. Such complexity, when combined with the myriad of possible time-based pricing strategy variations, results in a near limitless list of potential permutations. The process of selecting and adapting an appropriate shortlist of time-based pricing strategies to model is therefore an important one. Crucially the strategies selected for inclusion must meet the following criteria:

- They must be capable of reflecting the often short-term variation in supply from RES.
- They must be applicable adaptable to use in SAHES applications.

6.4.1 Evaluating the suitability of existing strategies

Using the selection criteria described above, it is possible to evaluate the suitability of the main forms of variable pricing prevalent in literature (Doostizadeh & Ghasemi 2012; Faruqui et al. 2009), which can be categorised as follows:

- Seasonal flat rate pricing
- Time of use pricing (ToU)
- Critical peak pricing (CPP)
- Real time pricing (RTP)
- Peak time rebates (PTR)

Seasonal flat rate pricing can be easily discounted due to the timescale at which variation in price occur. Given the need for short-term response to changing RES conditions, seasonal variations can be deemed insufficient.

Time of use pricing also initially appears unsuitable due to the fact that price only varies across a fixed number of fixed duration ‘blocks’. In the case of SAHES, this means that such a strategy would be unable to accurately reflect the energy price within any RES variation that took place within each of the fixed blocks. This issue could be addressed by making the pricing blocks vary in duration, which would lead to a more accurate representation of RES conditions. Time of use strategies also have the advantage of having a degree of flexibility when it comes to the principle timescale during which variations occur i.e. daily, weekly, seasonally etc.

Critical peak pricing can be seen as suitable given the potential for flexibility in the definition of how and when peaks are identified and announced. In SAHES applications, this could be done on a day-ahead or even hour-ahead basis, thus providing sufficient flexibility for the pricing to reflect both the magnitude and duration of peaks. As discussed above, critical peak pricing does not provide any scope for responsive consumers to reduce their energy bills, but instead promotes DR through consumer desire to avoid bill increases. Nevertheless, given the potential for CPP to promote considerable demand responses - as argued by (Newsham & Bowker 2010) - the decision was made to include critical peak pricing in the modelling process due to the possibility of it resulting in smaller bill increases than other variable pricing strategies.

Real time pricing can be seen as ideally suited to use in SAHES applications, given its ability to reflect both the magnitude and duration of system stress i.e. RES deficit, in energy price. It can therefore be seen as the form of variable energy pricing which most accurately reflects system conditions.

Peak time rebates differ from the aforementioned variable pricing strategies in that the financial benefits are offered on an *ex post* basis. The main limitation associated with its use in SAHES however is its reliance on a single, defined peak, during which rebates can be accrued through avoided consumption. Adapting such a strategy to increase the flexibility of this peak, or even creating the option for multiple peaks, was considered. However, the result was deemed too similar to time of use pricing, and peak time rebates were therefore discounted at this stage.

After this preliminary elimination process, the forms of variable pricing selected to for inclusion in the model (subject to adaptation) were therefore time of use (ToU), real time pricing (RTP) and critical peak pricing (CPP).

6.4.2 Adapting variable energy pricing for use in SAHES

Having identified three basic forms of variable energy pricing, the next task was to develop these conceptual approaches to variable energy pricing into clearly defined and robust strategies which could then be applied to the model.

Such an adaptation requires the consideration of a number of key elements of tariff design, namely the time period across which price variation will occur (or ‘price forecasting period’), and the advance notice of price variation that will be provided to consumers.

The price forecasting period represents the time period used to define the price variations issued to consumers. A shorter forecasting period is likely to include a narrower range of conditions and a greater level of confidence in the projections of both supply and demand conditions. Shorter forecasting periods are also likely to result in a greater frequency and magnitude of price variation, due to the fact that the range in pricing is spread over a narrower range of conditions.

The other key element of pricing strategy design is the amount of advance notice provided to consumers ahead of changes in price, which can range from hourly to seasonally. Generally speaking, longer advance notice periods are more likely to allow consumers to adapt and respond accordingly. However, longer notice periods also place more emphasis on the need for accurate forecasting, which itself is subject to inaccuracies. Shorter advance notice periods allow prices to reflect real-time conditions more accurately whilst placing less reliance on potentially inaccurate long-term forecasting, but give consumers less time to adapt their consumption behaviour in response to the resulting price variations.

For this particular modelling scenario it should be noted that the forecasting of both demand and RES conditions is assumed to be accurate.

In order to ensure that the results of the application of each strategy were directly comparable with the others, a level of standardisation was required. This was achieved in two ways. The first method involved the manipulation of the varying pricing levels used, such that the average price for each of the months in question was always equal to a pre-determined flat rate price (discussed in more detail below). This allowed a meaningful comparison to be made, not only between the developed variable pricing strategies, but between them and the flat rate pricing scenario which served as a base case. The ratio of minimum and maximum price levels was also kept constant in all strategies, given that differences in price form the basis of the consumer price elasticity used in the model.

6.4.3 Flat rate pricing

In order to provide a means of comparison, the first step in the development of pricing strategies is to apply a flat rate pricing strategy to act as a base case.

Flat rate energy tariffs are prevalent in most industrialised energy models, and reflect the average costs associated with the supply of energy services. This makes them simple to understand and easy to administer. In the case of large national/regional energy infrastructure, this approach means that communities which can be supplied at low cost to network operators pay the same rates as communities in more remote areas where the cost of supplying energy services can be considerably higher. This cost-spreading effect is less pronounced at smaller scales such as those of SAHES, where energy services are typically more costly to supply.

Eigg Electric, the community-owned company responsible for the management of the SAHES on the Scottish island of Eigg, uses a flat rate pricing strategy. The rate is designed to cover the initial project costs associated with the SAHES, pay the team of employees responsible for the ongoing operation and maintenance of the system, and to build up a fund for the replacement of system components in order to ensure the long-term sustainability of the project and the system. In 2008, when the system came online, Eigg Electric initially set their flat rate at £0.15/kWh. At that time, the average cost of domestic electricity in the UK was less than £0.13/kWh. By 2011 Eigg Electric had increased their price to £0.2/kWh (in order to cover the costs of, among other things, a previously un-planned expansion of their photovoltaic (PV) array). By 2013 this had again increased to £0.21/kWh, at a time when the UK average cost of electricity was approximately £0.15/kWh (DECC 2013). However, despite their prices being significantly higher than the UK average, estimates from Eigg Electric customers placed the cost of electricity under the new SAHES as being around a third of the cost before its implementation, when the most prevalent form of electricity generation was from generators which ran primarily on imported red diesel. It should also be noted that the introduction of the SAHES also brought increased security and reliability of supply.

For ease of comparison, and to provide some context, a flat rate price of 20p/kWh was chosen for the SAHES model. This figure represents the flat rate which all of the domestic consumers which comprise the model would pay under base case conditions. As the flat rate pricing scenario acts only as a base case against which to compare variable energy pricing strategies, the cost attributed to it can therefore be deemed inconsequential for the purposes of this study. Nevertheless, it was deemed appropriate to allocate a flat rate which fits within the context of the study.

6.4.4 Variable Time of Use (VToU) Pricing Strategy

As discussed in previous chapters, conventional ToU strategies typically involve splitting the time period in question (be it a season, a week, a day etc.) into blocks of fixed duration. These blocks can be seen as being defined relative to the expected demand curve only, given that supply is expected to meet demand. This means that the periods of high demand (normally during the evening) tend to coincide with higher pricing, and periods of low demand (late at night/early in the morning) with lower pricing. In the proposed context of SAHES however, the basis for price variation is the balance between demand and RES. This means that periods of high demand could potentially coincide with periods of high supply, resulting in minimal system stress and a limited need for DR. Given the inherent intermittency of RES, and therefore of the resulting periods of imbalance, the use of fixed blocks of time can be seen as inappropriate in this context. In order to be used effectively in such a changeable environment, any ToU strategy must have the ability to determine the following:

- When price changes occur.
- The duration of each pricing period.
- The number of price changes which can occur each day.

Such a strategy is therefore more complex and more variable than most conventional ToU pricing structures, and could even be seen as more closely resembling RTP (in which price fluctuates in ‘real time’). However, due to the limited number of pricing increments proposed (three: off-peak, shoulder and peak) this strategy is referred to as Variable Time of Use (VToU).

The first step in defining the pricing under the VToU strategy is to quantify the total range of RES deficit/surplus values forecast for the month in question, spanning from peak RES deficit to peak RES surplus. This ‘deficit range’ is then split into three equally sized segments, with the segment encompassing the highest deficit figures being allocated the highest ‘peak’ price, and the highest surplus values being allocated the lowest ‘off-peak’ price. The middle third is allocated a ‘shoulder’ pricing level, which falls mid-way between the peak and off-peak prices. This preliminary pricing structure is then applied to the month’s RES and community energy demand forecasts, so that the pricing levels themselves can be adjusted such that the mean price is equal to the base case flat rate price of £0.2/kWh. This process is shown in Figure 6-9.

This method of price setting ensures that the price of energy remains consistent throughout the year, by reducing the scope for extended periods of low or high pricing. If, for example, prices were set on an annual basis, seasonal variations in RES output would lead to prolonged periods of low/high pricing e.g. the seasonal variation in output from PV would lead to lower prices in summer than in winter in SAHES featuring significant amounts of PV generation. By setting prices on a monthly basis, the deficit range which corresponds to each pricing increment is also smaller, thereby giving more scope for price variation and therefore DR.

It should be noted that for the purposes of this study, both demand and RES forecasting are assumed to be accurate. However, in real-life applications the inherent uncertainty associated with forecasting both RES and domestic demand would mean that a more detailed approach would be required when defining the price of energy for each individual day. This could be provided through the use of a day-/week-ahead forecast of both RES and demand, which would provide a more accurate basis for price setting. This would lead to an additional stage in the price setting process, as illustrated in Figure 6-10, which shows how the monthly setpoint process described above could be combined with day-ahead forecasting to create a daily RES deficit profile and therefore a more accurate price profile, which is then communicated to consumers, thereby facilitating DR.

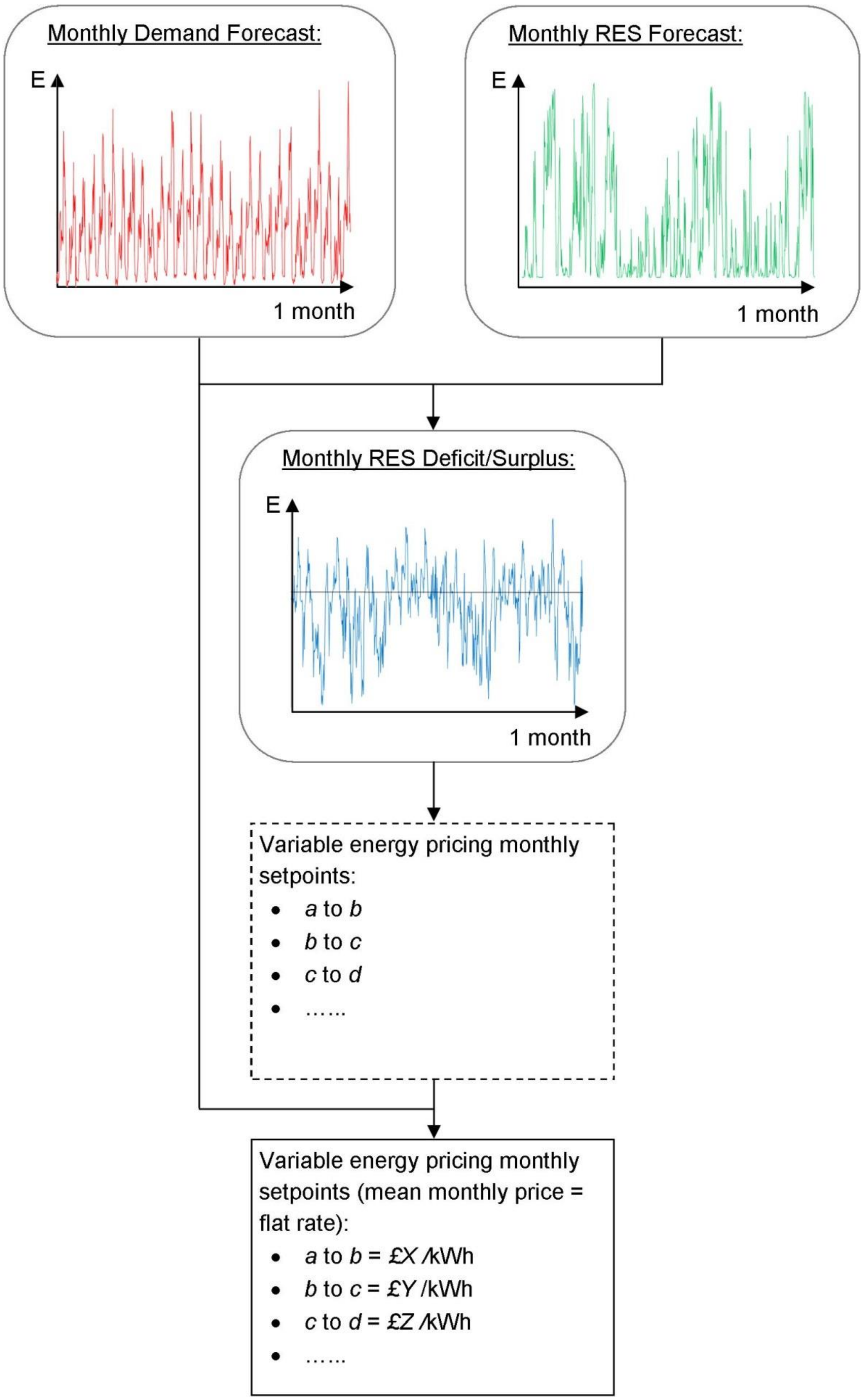


Figure 6-9 - Illustration of the price setting process, based on monthly forecasts.

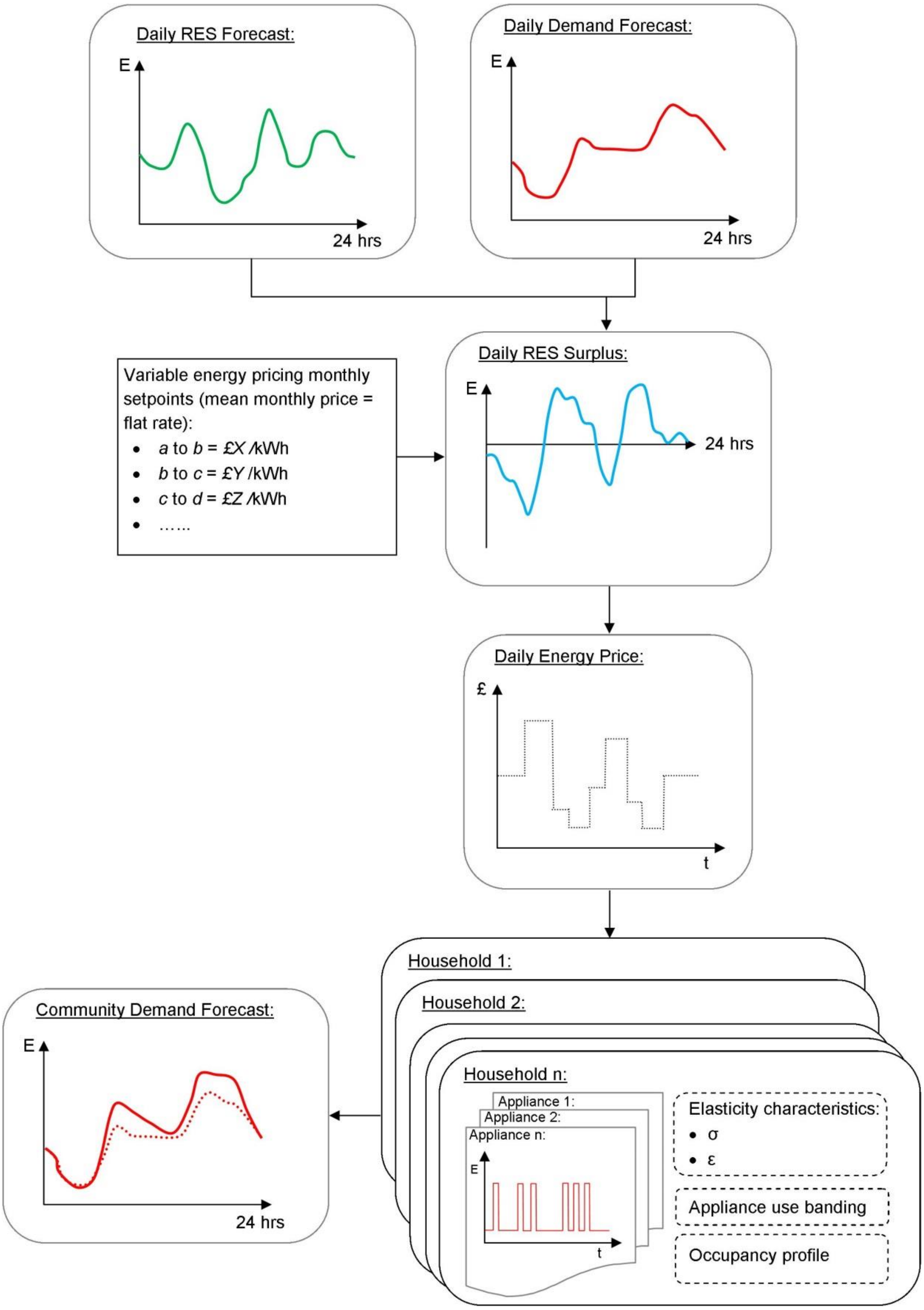


Figure 6-10 - The combination of monthly and daily forecasting processes, and the application of variable pricing resulting in DR.

In order to further demonstrate how VToU is implemented in the SAHES model, let us consider the case of an autumn day. The pricing levels for the month in question (in this case September) are set based on the process outlined above, with a maximum predicted RES deficit of 225.6kW and a maximum predicted surplus of 339.8kW. This range of values is then split into three equally sized segments, each with its own corresponding price, as shown in Table 6-5.

Table 6-5 - VToU pricing structure for an autumn day, based on a projected monthly RES deficit range (negative values indicate surplus).

Price level		Deficit Range (kW)	
		Max.	Min.
Off-peak:	£ 0.096	-339.8	-151.4
Shoulder:	£ 0.192	-151.4	37.1
Peak:	£ 0.288	37.1	225.6

As described above, the pricing levels are set such that the mean monthly price of energy is equal to the base case flat-rate value of £0.2/kWh[1]. The fact that the shoulder level price assigned in Table 6-5 is lower than the base case flat rate price reflects the fact that an overall RES surplus is predicted during the month in question.

Having defined the cut-off points for each pricing increment, the price of energy is then set depending on which of these three brackets the predicted RES deficit falls into during any given hour. This is further illustrated in Figure 6-11, which shows the predicted RES deficit values which result from maximum RES conditions during an autumn day. This shows the projected RES deficit spanning all three pricing levels (note that the maximum projected RES surplus of 225.6kW is not reached during this day, but that the maximum projected RES defict of 339.8kW is reached). Figure 6-12 shows the resulting price plot under VToU.

[1] This process will be applied to all of the developed variable pricing strategies. The ratio between the maximum and minimum pricing levels will also remain constant across all the strategies. The importance of this price ratio, and more specifically the impact of altering it, is covered in more detail in Chapter 8.

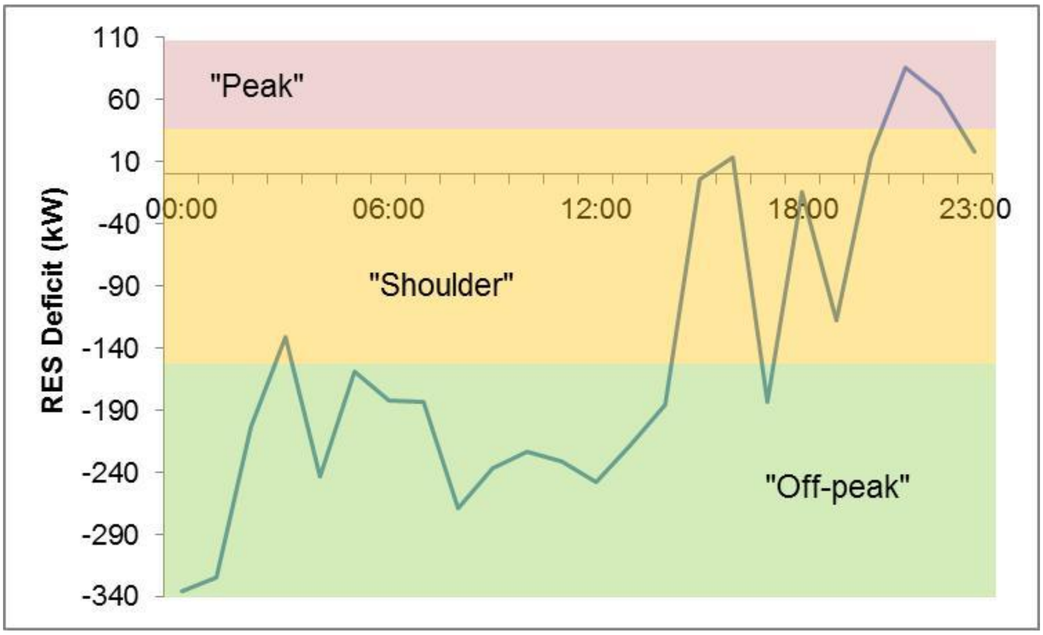


Figure 6-11 - Graph showing predicted RES deficit during maximum RES conditions on an autumn day, and the corresponding VToU pricing levels.

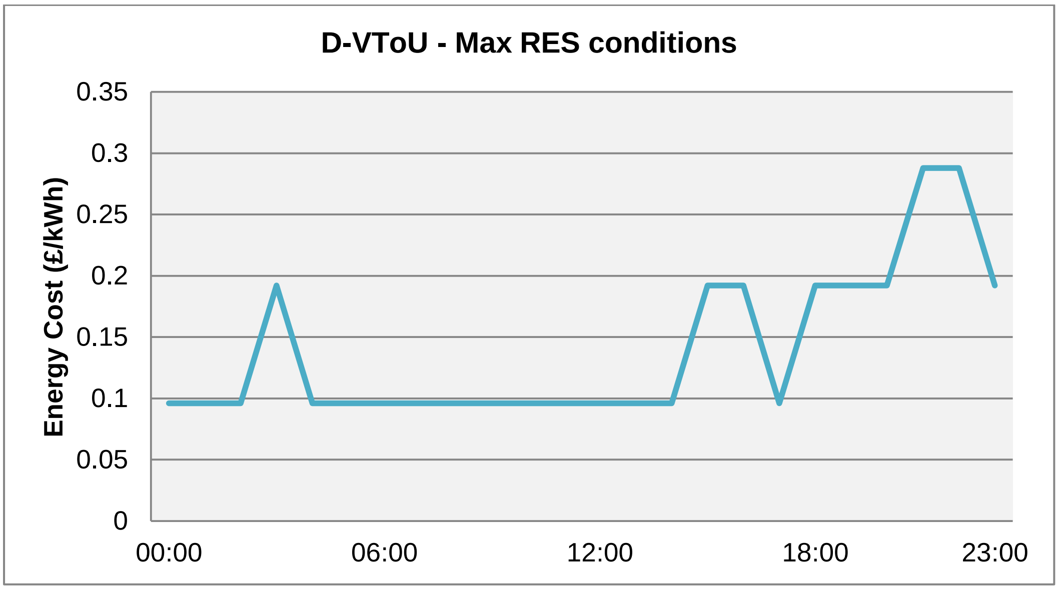


Figure 6-12 - Graph showing VToU pricing profile during maximum RES conditions for an autumn day.

The graphs above illustrate the extent to which the VToU strategy reflects RES deficit/surplus. Maximum RES conditions as shown above result in a daily mean energy price of £0.140/kWh. Meanwhile, the same demand profile occurring during minimum RES conditions would result in a daily mean price of just £0.220/kWh, with no occurrences of the off-peak pricing throughout the whole day.

6.4.5 Variable Critical Peak Pricing (VCPP) Strategy

The design of the VCPP strategy is similar to that of the VToU strategy presented above, but with greater emphasis placed on avoiding RES deficit. This means that instead of uniform increases and decreases in price, the price increases sharply as RES deficit increases.

The VCPP strategy features a base pricing rate, which is applied during all periods of predicted RES surplus. This base rate is then increased during times of predicted RES deficit. Three further pricing levels have been included, which are defined relative to the predicted maximum RES deficit for the month in question. The first of these is applied during periods where a RES deficit is predicted to occur, the magnitude of which is less than 50% of the predicted monthly maximum. The second level of increase is applied when deficit is predicted to be between 50% and 75% of the predicted peak, with the third being applied when RES deficit exceeds 75% of the predicted peak.

Let us again consider an autumn day demand scenario, this time under the VCPP strategy. Once again, the monthly predicted RES deficit/surplus values are calculated on an hourly basis, with a maximum RES deficit of 207.1kW. This figure is used to define the cut-off points for each of the three increased pricing levels (with the fourth - the base rate - being applied during all instances of predicted RES surplus). The resulting pricing levels and the range of RES deficit values to which each applies are shown in Table 6-6.

Table 6-6 - VCPP pricing structure for an autumn weekday, based on projected RES deficit levels.

Pricing Rate	Applicable	RES deficit range		Price (£/kWh)
		Minimum	Maximum	
Base Rate	Surplus only	n/a	0	£ 0.180
Low Peak	<50% max. monthly deficit	0	103.6	£ 0.216
Mid Peak	50-75% max monthly deficit	103.5	155.3	£ 0.360
High Peak	>75% max monthly deficit	155.3	207.1	£ 0.540

As with the VToU strategy described above, VCPP pricing levels are set such that the average energy price over the month is equal to the base case flat rate of £0.2/kWh, in order to maintain comparability between pricing strategies and the flat rate base case. The maximum ‘High Peak’ price is therefore defined as being three times that of the minimum ‘Base Rate’ price, with the ‘Mid Peak’ price being midway between the two. The ‘Low Peak’ price is defined by adding 10% of the difference between the minimum and maximum prices to the base rate. Figure 6-13 and Figure 6-14 show the daily RES deficit plot associated with minimum RES conditions during an autumn day, and the resultant price plot under VCPP.

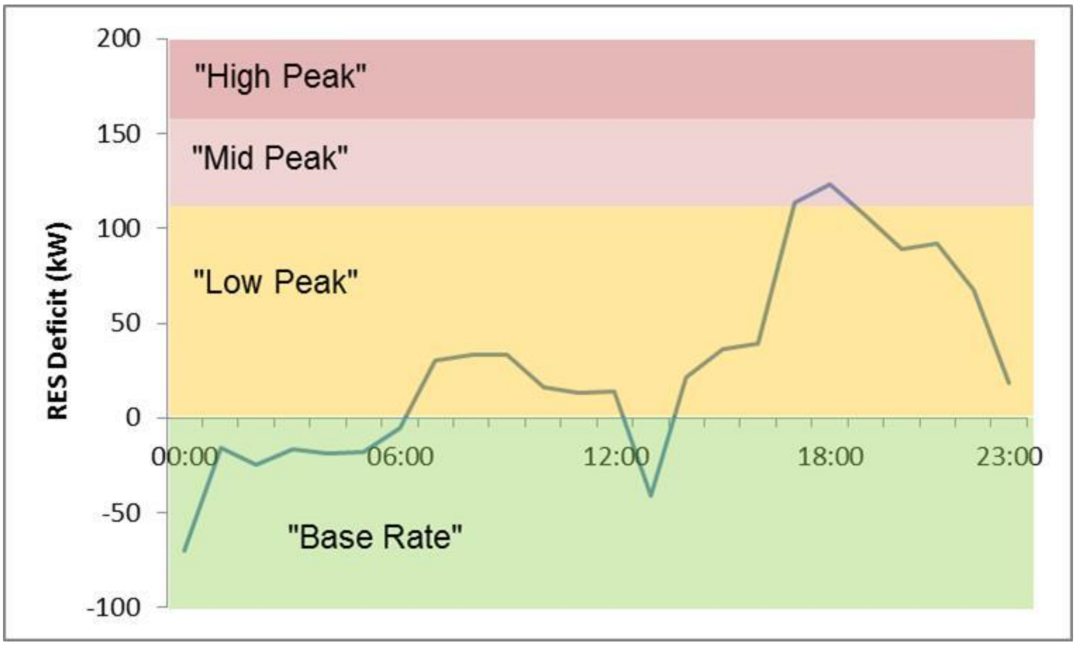


Figure 6-13 - Graph showing predicted RES deficit during minimum RES conditions on an autumn day, and the corresponding VCPP pricing levels.

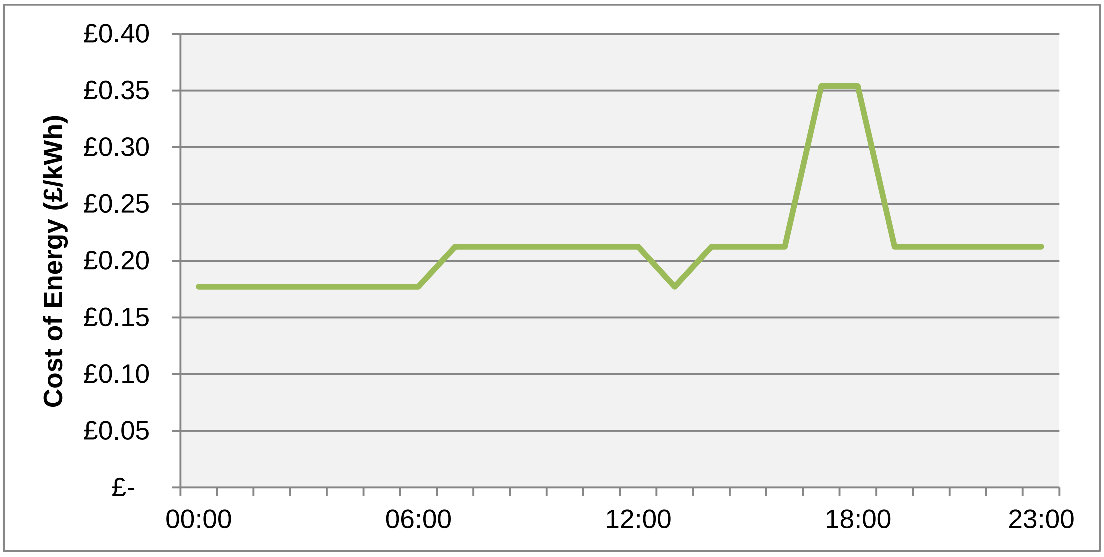


Figure 6-14 - Graph showing VCPP pricing profile during minimum RES conditions for an autumn day.

The minimum RES conditions shown above result in a mean daily price of £0.212/kWh. The triggering of the ‘Mid Peak’ pricing level is clearly identifiable between the hours of 17:00 and 18:00. The same autumn day demand under maximum RES conditions fails to trigger ‘Mid’ or ‘High’ peak pricing, and instead sees prices fluctuate between 'Base Rate' and 'Low Peak', as shown in Figure 6-15. This results in a daily mean price of £0.184/kWh.

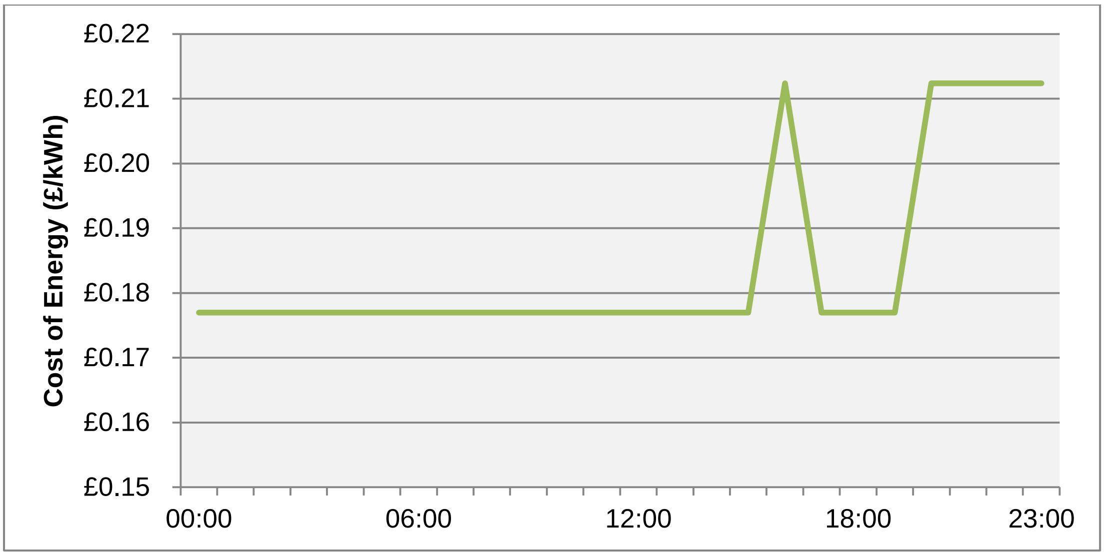


Figure 6-15 - Graph showing VCPP pricing profile during maximum RES conditions for an autumn day.

6.4.6 Real Time Pricing (RTP) Strategy

As with VToU and VCPP, the RTP strategy developed for use in the SAHES model also uses projected RES deficit/surplus as the basis for price variations. Pricing levels are once again based on predicted hourly RES deficit/surplus levels for the month in question, with a total of ten pricing increments separating the maximum predicted RES surplus value from the maximum predicted RES deficit. This results in a level of representation of the predicted RES deficit/surplus profile which is more accurate than under the VToU. Once again, the level of these pricing increments is such that the average monthly price under the RTP strategy is equal to the flat rate base case price of £0.2/kWh.

In the case of the autumn day describe above, the resulting RTP pricing structure for the month in question (September) is shown in Table 6-7. The resulting price plots for both minimum and maximum RES conditions are shown in Figure 6-16 and Figure 6-17.

Table 6-7 - RTP pricing structure for an autumn day, based on projected RES deficit levels (negative number represent RES surplus).

Price (£/kWh)	Deficit Range (kW)	
	Max.	Min.
£ 0.290	225.6	169.0
£ 0.268	169.0	112.5
£ 0.247	112.5	56.0
£ 0.225	56.0	-0.6
£ 0.204	-0.6	-57.1
£ 0.182	-57.1	-113.7
£ 0.161	-113.7	-170.2
£ 0.139	-170.2	-226.7
£ 0.118	-226.7	-283.3
£ 0.097	-283.3	-339.8

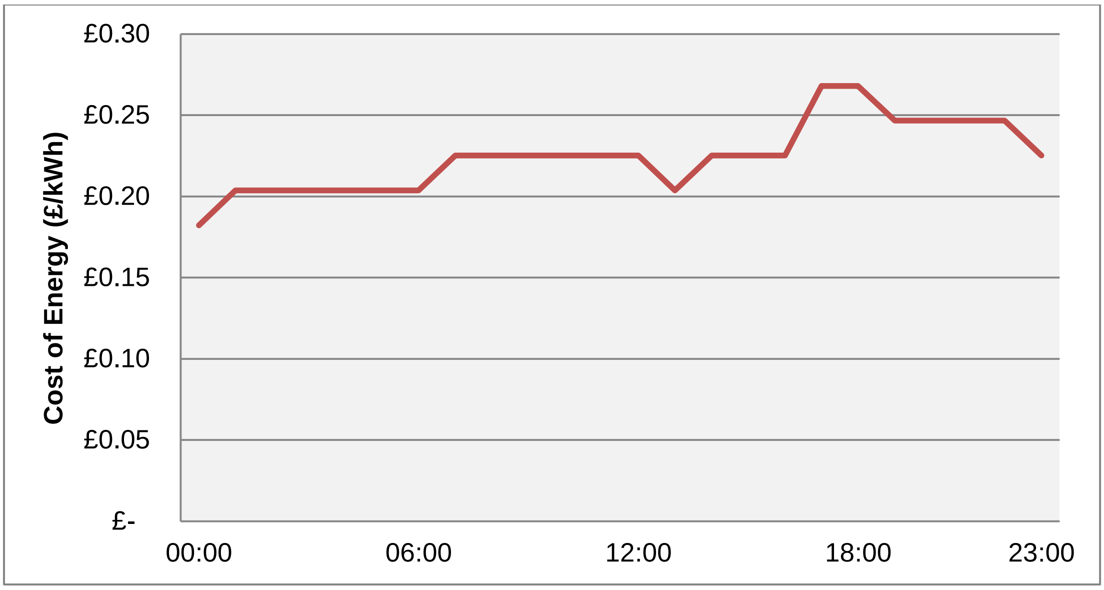


Figure 6-16 - Graph showing RTP pricing profile during minimum RES conditions for an autumn day.

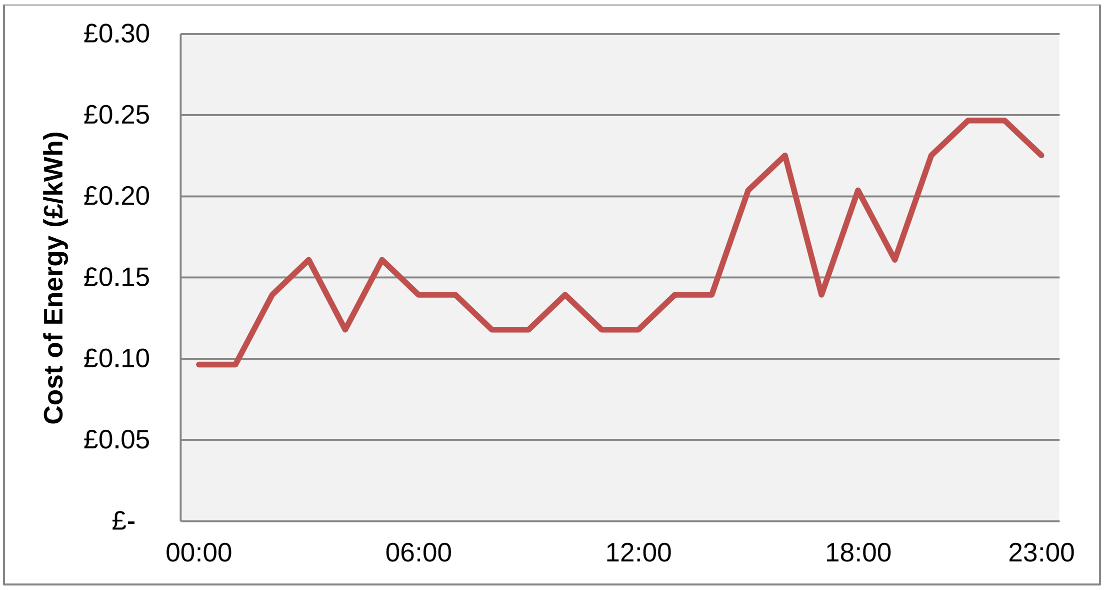


Figure 6-17 - Graph showing RTP pricing profile during maximum RES conditions for an autumn day.

As is clear from the graphs above, the RTP strategy results in prices which fluctuate more regularly and less uniformly than under VToU and VCPP.

6.4.7 Preliminary strategy comparison

Having defined the structure and implementation of each of the developed variable pricing strategies, it is possible to conduct a preliminary comparison of the three and to identify the key differences between them.

Both the VToU and RTP strategies place emphasis on ensuring that energy prices reflect RES deficit/surplus levels as closely as possible, with the primary difference between the number of pricing increments available to each (three for VToU and ten for RTP). RTP can therefore be seen as being the most effective of the strategies at reflecting RES deficit/surplus levels in the price of energy. The VCPP places the emphasis not on reflecting the RES deficit/surplus, but on the avoidance of high levels of RES deficit in particular. For this reason, VCPP could be seen as neglecting the potential for load growth during times of high RES surplus (which would be facilitated by reducing energy prices) in favour of maximising the potential for load shifting and curtailment during times of RES deficit.

6.5 DR Algorithm Development

Having established demand and supply profiles and sized an appropriate SAHES, and having identified and adapted three different forms of variable energy pricing, the last stage of the model development involves the development of an algorithm which could be used to apply the variable pricing strategies to the base case model and enact the response of the consumers featured in it. This represents the key capability of the model - the ability to apply variable pricing strategies, calculate the extent of the resulting DR at an individual household level, and then apply the resulting changes in demand. These household profiles can then be aggregated into community-wide demand profiles, allowing the impact of DR to be assessed at a community/system-wide level. The DR implemented by the algorithm consists of three elements: load shifting, load curtailment and load growth, and these are carried out in this order on a household-by-household basis.

A number of programs were evaluated when it came to selecting a tool with which to develop and implement the DR algorithm. This needed to be capable of handling the high volume of processes and iterations required for the simulation of the SAHES model, and be capable of providing the required detail and computational speed in a simple and easily replicable way. Given the range of sources involved in the SAHES model (such as HOMER, the Richardson model etc.) the selected tool also needed to be capable of importing and exporting data in a range of accessible formats. The tools considered ranged from a simple spreadsheet to more complex programming tools such as C++ and python. However, MATLAB was found to offer the required level of programming detail, whilst also being capable of automating both data entry and output through spreadsheets.

6.5.1 Algorithm input data

In order to enact household (and community) DR, the model requires specific input data which, when combined with household characteristics such as appliance use and demand flexibility, determines the extent to which each household responds to price variation. This input data can be split into two categories: that which depends on individual household characteristics and that which applies to the community as a whole. The former includes the household characteristics described earlier in this chapter, such as appliance use and household demand elasticity bandings. The latter refers to the energy pricing issued to consumers in advance, which varies according to the pricing strategy being implemented in any given simulation.

6.5.2 Load shifting

Shifting a load from one time period to another represents a key strategic response to changing energy price signals which, unlike both curtailment and growth, does not result in a change in overall energy consumption. Through such flexibility, load shifting enables consumers to shift loads away from periods of high energy price to periods of lower price, thus reducing the cost associated with the load in question whilst still ensuring that the demand in question is met. From the perspective of the energy system and its operators, load shifting serves to reduce the peak demands placed on the system, thereby reducing system stresses and potentially reducing the need for energy storage and/or back-up generation capacity. Within SAHES, it is equally important from a load-building perspective i.e. to increase consumption during times when supply exceeds demand.

The appliances which are defined as being shiftable in the model are electric space heating (when used), dish washers, washer dryers, washing machines. All of these appliances are identified by Pipattanasomporn et al. as being suitable for DR (Pipattanasomporn et al. 2014). It should also be noted that these are not the only appliances available for DR actions - others have been selected for load curtailment and growth, and are presented in sections 6.5.3 and 6.5.4 respectively.

Each of these appliances also has an associated shift priority, which dictates the order in which they are assessed for load shifting viability. This ensures that in cases which only allow for the shifting of a limited number of loads, the loads with the highest ranking take priority and are shifted first.

While these appliances have been identified as being suitable for load shifting within the model, it should be noted that this is likely to vary, perhaps significantly, in practice. With this in mind, the appliances which are deemed shiftable, curtailable and growable in the model varies according to household elasticity bandings, with each banding having a different list of appliances, with different shift/curtailment/growth priorities. This is illustrated in Table 6-8, which shows the appliances which are shiftable in green for each of the three household elasticity groups. The shift priority assigned to each appliance is also shown e.g. the first appliance to be shifted by medium elasticity households is the dish washer, followed by the washer dryer and lastly electric space heating. By introducing this additional variation to the way in which households are likely to engage in DR, the model reflects the likelihood that different households will choose to enact DR in different ways.

Table 6-8 - Breakdown of shiftable appliances under the three household elasticity bandings, and the priorities assigned to each.

	Elasticity scenario		
	Low ε	Med ε	High ε
Dish washer	×	1	×
Washing machine	×	×	1
Washer dryer	1	2	×
Electric space heating	2	3	2

In order to reflect the likelihood that the shiftable appliances will be brought forward/deferred to varying extents, a maximum temporal shift was selected for each appliance, as shown in Table 6-9. This reflects the fact that some appliance loads can be shifted more easily than others without having an overly detrimental effect on consumer utility and comfort. This also enables the temporal shift available for each of the appliances to vary according to household elasticity banding. The only appliance which does not see temporal shift increase as household elasticity increases are dishwashers, which are classed as shiftable for households in the medium elasticity banding, but curtailable for those in the high elasticity banding.

Table 6-9 - The maximum temporal shift available for each shiftable appliance, according to household elasticity banding.

Shiftable Appliance	Maximum temporal shift (hrs)		
	Low ε households	Med. ε households	High ε households
Washing machine	0	0	6
Washer dryer	2	4	6
Dish washer	0	4	0
Elec. Space Heating	1	2	3

The load shifting algorithm deployed in the model is shown in Figure 6-18, and is applied at the household level. The algorithm requires the hourly disaggregated load profile of the house in question (i.e. an appliance-level breakdown of demand), the daily pricing profile for the day in question as well as the household and community characteristics described above.

The algorithm first selects the shiftable appliance with the highest ‘shift priority’ rating, and identifies if and when that appliance is active during the day in question (if no shiftable appliance are active during the day, the algorithm moves on to the next stage of the DR process). The algorithm then selects the first of the appliance’s forecasted load cycles e.g. a 2 hour cycle for a washing machine, and determines all the potential shift locations available. This is governed by the maximum number of hours by which the appliance’s loads can be shifted - a product of the household’s elasticity banding - and the occurrence of other forecasted load cycles e.g. a second use of the washing machine later in the same day. The variable pricing profile is then applied, and the cost of the load cycle in each of the potential shift locations is calculated. If a potential shift location would result in a decrease in the cost of the load cycle relative to that which was originally forecasted and the shift in question is within the limits set out by the price elasticity of demand equation, then it is deemed viable and added to a shortlist. The optimum shift location is therefore that which achieves the greatest reduction in the cost of the load cycle. The optimum shift is then executed, and the new demand profile saved. This process is then repeated for all active load cycles which occur during the day in question and for each of the shiftable appliances in turn, according to their order of shift priority. It should be noted that the equation for the elasticity of substitution which is used to determine the maximum load that can be shifted works on a cumulative basis. This means that there is a maximum shiftable 'allowance', which will be used up as more load cycles are shifted.

Note that the shifting of loads is limited to the day for which each load is scheduled. As a result, the shifting of loads from one day to another is not facilitated by the model.

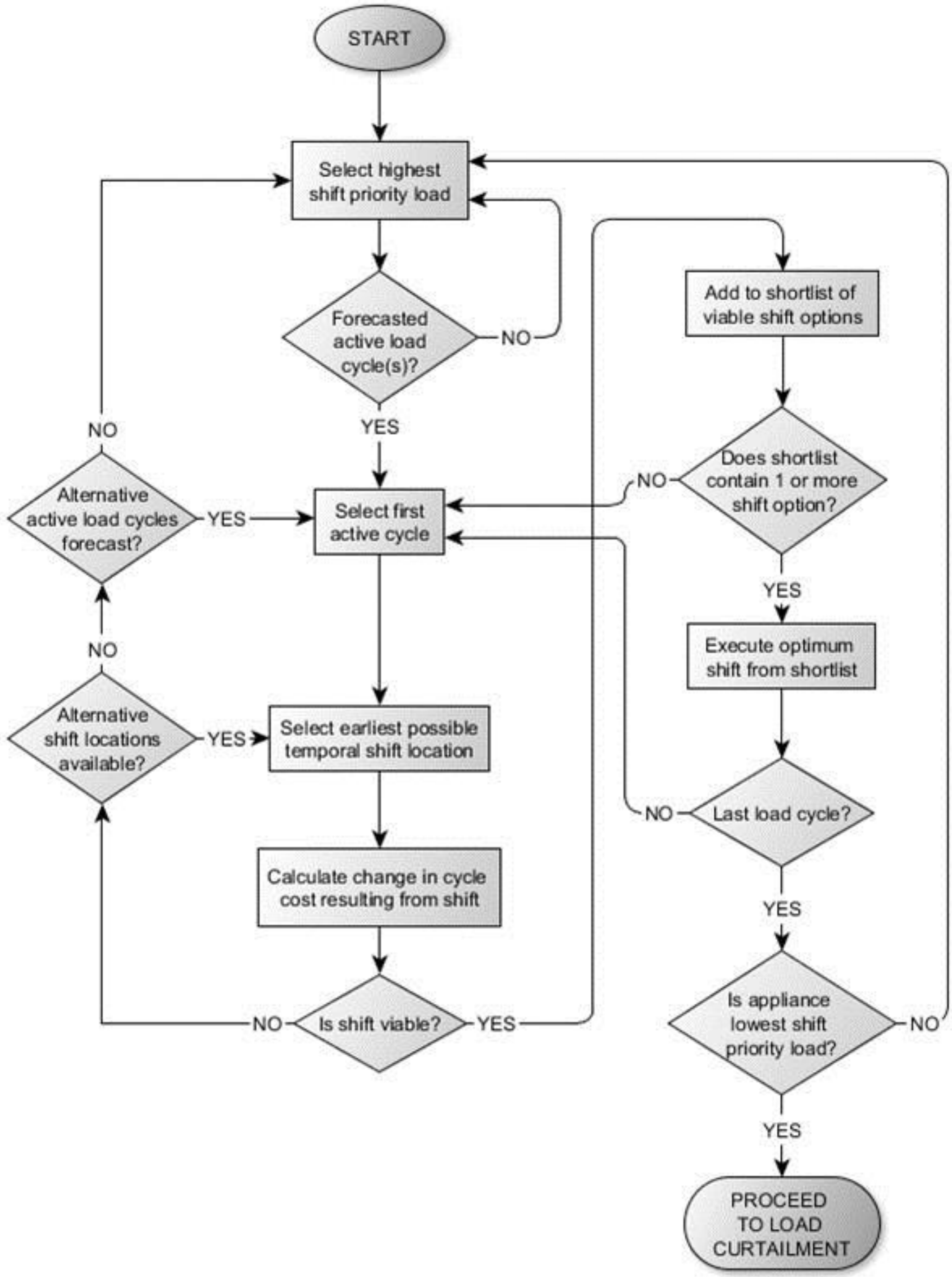


Figure 6-18 - Load shifting process algorithm.

6.5.3 Load curtailment

Following the completion of the load shifting algorithm, the DR process moves on to identify opportunities for load curtailment i.e. loads which can be shortened or removed altogether. The loads which were identified as being curtailable are as follows:

- Iron
- Vacuum cleaner
- Second and third TV's
- Small cooking appliances
- Dishwasher
- Tumble dryer

These have been identified as loads which are non-essential, and which could be shortened in order to avoid high load cycle costs. As with the shiftable loads, curtailable loads are ranked in order of the priority in which they are curtailed.

Table 6-10 - Breakdown of curtailable appliances under the three household elasticity bandings, and the priorities assigned to each.

	Elasticity scenario		
	Low ε	Med ε	High ε
Iron	×	×	2
Vacuum	×	1	3
TV 2	×	2	1
TV 3	×	×	4
Small cooking (group)	×	×	5
Dish washer	×	×	6
Tumble dryer	×	×	7

The curtailment algorithm works in much the same way as the load shifting algorithm, in that the curtailable loads are ordered according to the priority in which they will be curtailed. The algorithm distinguishes between appliances whose load cycles are totally curtailable and those which are partially curtailable, with the latter being reduced in duration an hour at a time. The curtailment algorithm is shown in Figure 6-19.

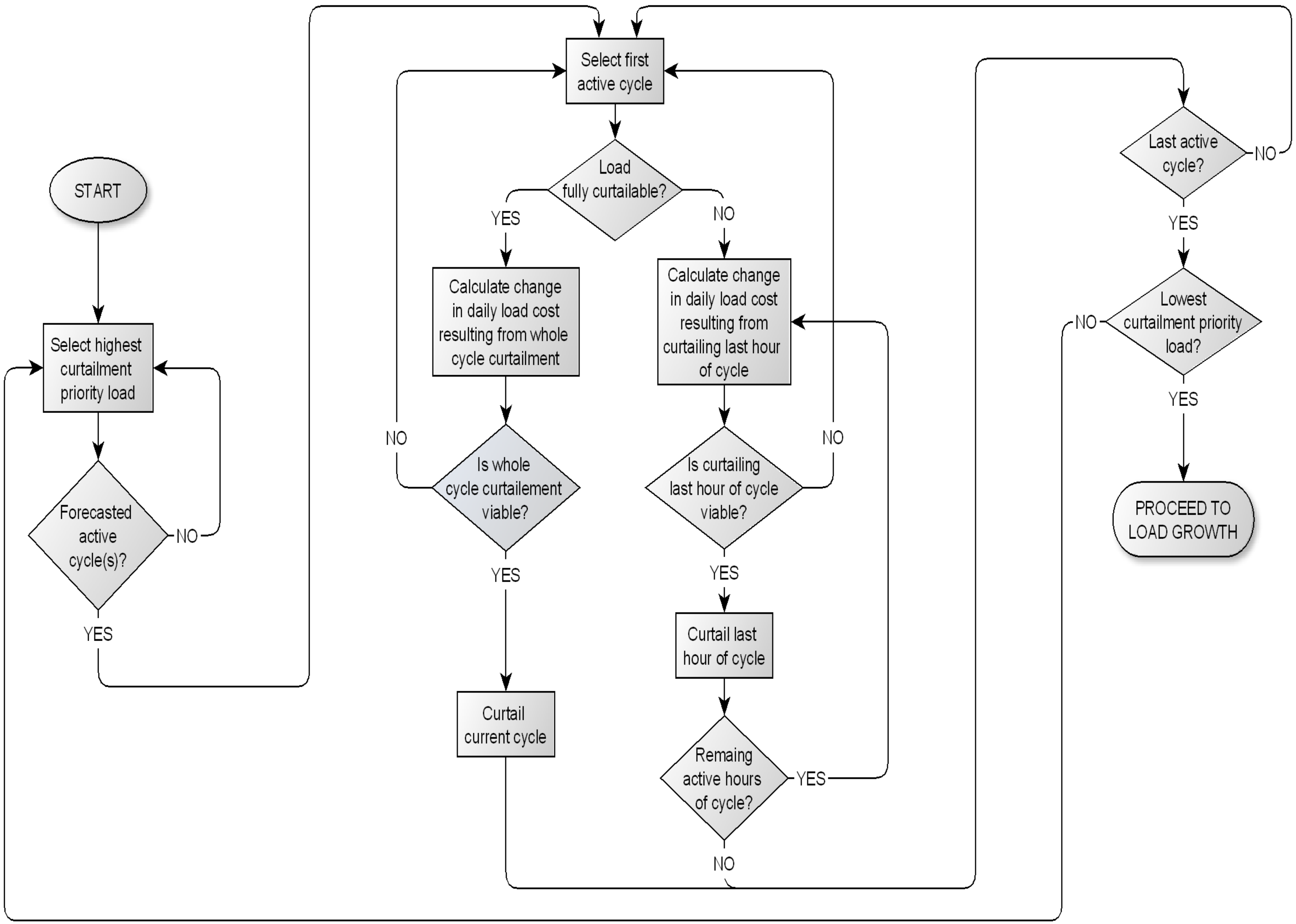


Figure 6-19 - Load curtailment process algorithm.

6.5.4 Load growth

The load growth algorithm can be seen as the curtailment algorithm in reverse, whereby the duration of appliance load cycles is increased instead of decreased. The loads identified as being 'growable' for the purposes of this study are television loads. This was chosen as it was considered to reflect the type of non-critical appliance use which may be influenced by energy price. In real-world applications, this may also include plug-in appliance loads such as the charging of electronic devices. Table 6-11 shows the assignment of growable loads under each of the household elasticity bandings, and their associated priorities.

Table 6-11- Breakdown of growable loads under the three household elasticity bandings, and the priorities assigned to each.

	Elasticity scenario		
	Low ε	Med ε	High ε
TV 1	1	2	3
TV 2	×	1	2
TV 3	×	×	1

The load growth algorithm follows largely the same process as the curtailment algorithm described above. In order to prevent load cycles from spreading out with the day in question, load cycles which are forecasted to end during the last hour of the day are not allowed to be lengthened. Load growth is deemed viable if the potential increase in load cycle duration does not cause the maximum permissible load growth for the household to be exceeded. As previously, this maximum permissible value works on a cumulative basis, meaning that lower priority loads are more likely to be deemed non-viable. The other deciding factor in determining the viability of load growth is the price of energy for the hour(s) into which the load cycle will extend. If the price in the hour following the last forecasted hour of the load cycle is lower than the average hourly price for the original (un-extended) load cycle, then the growth is deemed viable. The load growth algorithm is shown in Figure 6-20.

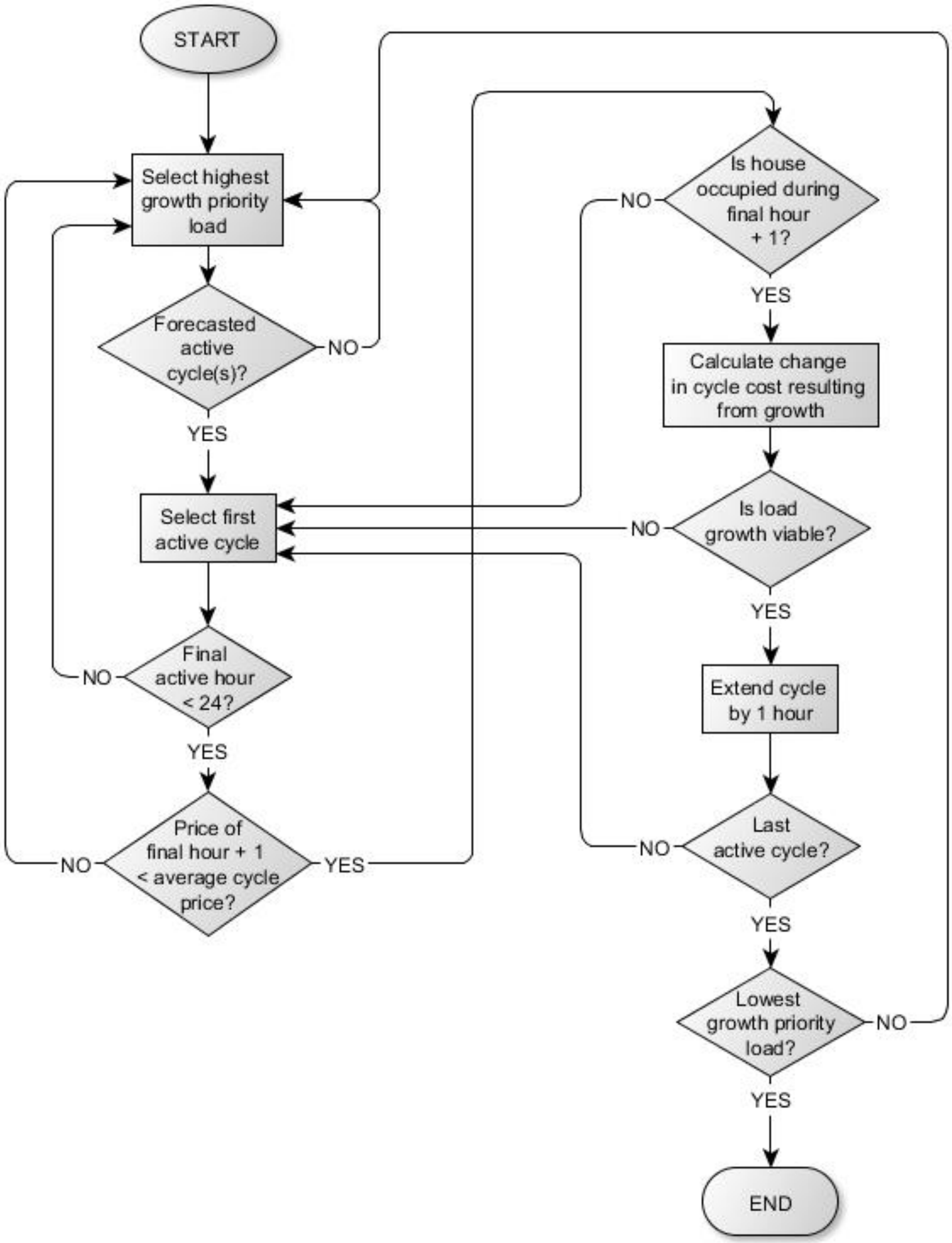


Figure 6-20 - Load growth process algorithm.

6.5.5 DR algorithm verification

Before the DR algorithm can be applied to the model and the resulting DR quantified and analysed, it is necessary to verify its effectiveness.

As discussed in section 6.1.1, Sargent's modelling methodology (Sargent 1981) sets out three main steps to model validation. The first of these relates to the conceptual model, which represents the mathematical/logical representation of the problem entity (in this case a generic SAHES). This involves the verification of the number and size of households featured in the demand model, and the appliance ownership and consumption profiles associated with each of the appliances featured within the Richardson model used to compile the high resolution domestic consumption models. This process was largely literature based, and incorporates certain outcomes of the consumer survey presented in Chapter 5, such as the spread of household sizes. This stage of the model validation also involves the DR algorithms and pricing strategies, both of which were also subject to additional validation steps later in the process.

The second validation stage relates to the computerised model, in order to ensure that conceptual models featured are correctly implemented. This primarily relates to the DR algorithms and the setting of pricing levels for each of the three strategies developed. This was conducted using a predictive validation approach, whereby each of the three variable pricing strategies was applied to a single household. The resulting changes in demand (measured at a single appliance level) were then compared with hand calculations, to ensure that both the pricing levels and the DR actions which occur as a result were implemented correctly. The household selected for this task has considerable scope for all three forms of DR (load shifting, load curtailment and load growth) due to the fact that it is a four-person household which falls within the high elasticity group and has a high level of appliance use. The base case demand profile (generated by the Richardson model) is shown in Figure 6-21.

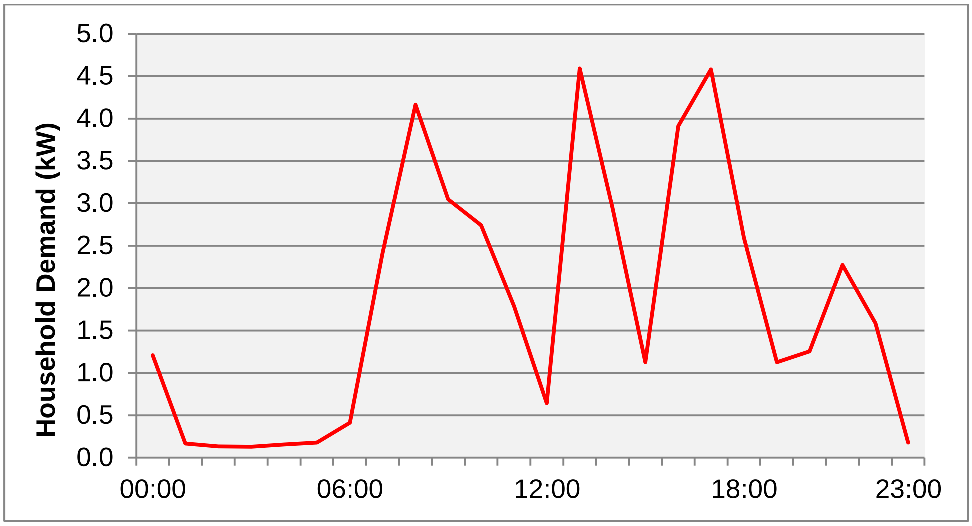


Figure 6-21 - Graph showing the base case demand profile of the household used in the predictive validation process.

Figure 6-22 shows the impact of the introduction of the VToU pricing strategy on the demand profile of the household in question.

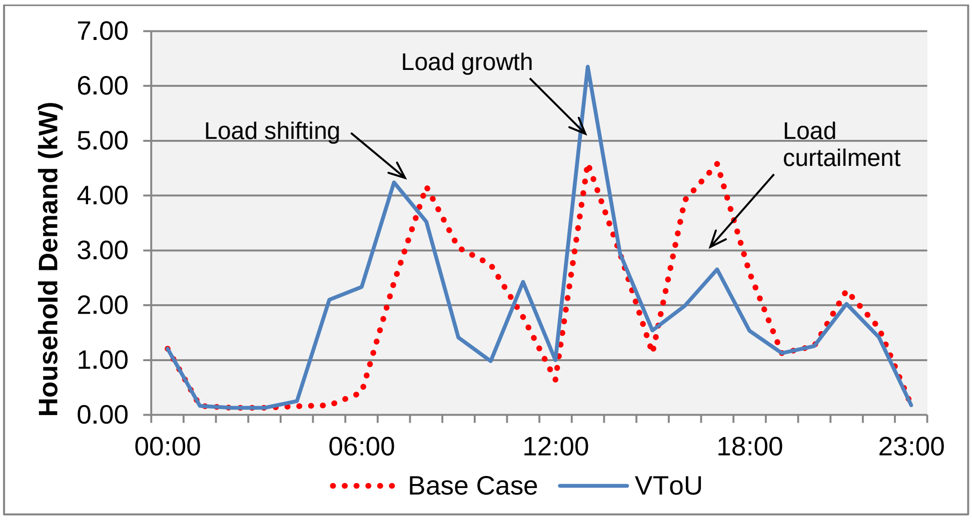


Figure 6-22 - Household DR under VToU during an autumn day under maximum RES conditions - the result of the predictive validation process.

The shifting, curtailment and growth of loads which occur as a result of the implementation of all three pricing strategies were found to directly correspond with those calculated manually. At least one instance of each can be seen in Figure

6-22. Table 6-12 shows the total hourly demand of the household in question under both base case and VToU pricing scenarios. Hourly demand can be seen to increase and decrease by as much as 1.92kWh during a given hour, with an overall decrease in daily energy demand of 0.41kWh. This table also provides further evidence that all three DR algorithms (load growth, load curtailment and load shifting) are being implemented effectively.

Table 6-12 - Comparison of base case hourly household demand with demand under VToU.

Time	Demand (kWh)		Change in demand
	Base Case	VToU	
00:00	1.21	1.21	0.00
01:00	0.17	0.17	0.00
02:00	0.13	0.13	0.00
03:00	0.13	0.13	0.00
04:00	0.16	0.25	0.10
05:00	0.18	2.10	1.92
06:00	0.41	2.33	1.92
07:00	2.41	4.24	1.83
08:00	4.17	3.52	-0.64
09:00	3.05	1.42	-1.63
10:00	2.74	0.98	-1.76
11:00	1.79	2.43	0.64
12:00	0.64	1.00	0.35
13:00	4.59	6.35	1.76
14:00	2.94	2.94	0.00
15:00	1.13	1.54	0.42
16:00	3.91	1.99	-1.92
17:00	4.58	2.66	-1.92
18:00	2.59	1.54	-1.06
19:00	1.12	1.12	0.00
20:00	1.25	1.25	0.00
21:00	2.27	2.03	-0.25
22:00	1.59	1.42	-0.17
23:00	0.18	0.18	0.00
TOTAL	*43.33*	*42.92*	*-0.41*

This process was repeated for multiple households, and under all four seasonal days and RES scenarios, so as to ensure that all aspects of the DR algorithms and pricing strategies were correctly implemented within the model.

The last step in the validation of the SAHES model involves verifying operational validity i.e. ensuring that the outputs provided by the model satisfy the requirements of the project. This is by nature a more iterative process, which encompassed much of the aforementioned model development and validation processes, which help to ensure that the developed model is capable of providing accurate and concise results data which is relevant and specific to the main research question.

6.6 Conclusions

This chapter has defined the aims and objectives of the modelling process, including the selection of an appropriate modelling methodology.

The first step in the modelling process, as outlined in Sargent's methodology, is the creation of a conceptual model which can be deemed to be representative of the problem entity in question (in this case a SAHES). In order to provide the context for the model, a notional SAHES has been developed. This notional SAHES has been appropriately sized using existing software tools, and the associated energy demand and supply profiles developed accordingly. In addition, the likely variation in both energy consumption and in attitude and response towards variable pricing in real-life SAHES has been replicated, so as to achieve sufficient diversity of demand. This has been achieved by introducing variability in appliance use, occupancy, household size and price elasticity of demand values.

A total of three variable energy pricing strategies have been developed, which have been adapted from the conventional forms of variable pricing summarised in the previous chapter. These are applied to the base case model in the following chapter, and the resulting DR analysed.

Lastly, and perhaps most importantly, this chapter has described the design, development and verification of the three forms of DR featured in the model, and the process through which they are applied to the base case model in order to represent the response of domestic consumers to variable energy prices.

The twin outputs of the work described in this chapter are the DR algorithm, and the model to which it can be applied. This represents the completion of the computerised model described in Sargent's methodology. The next chapter presents the experimentation phase, which involves using the computerised model to simulate DR under a range of scenarios and conditions.

6.7 References for Chapter 6

Al-Karaghouli, A. & Kazmerski, L.L., 2010. Optimization and life-cycle cost of health clinic PV system for a rural area in southern Iraq using HOMER software. *Solar Energy*, 84(4), pp.710–714. Available at: http://www.sciencedirect.com/science/article/pii/S0038092X1000037X.

Arteconi, A., Hewitt, N.J. & Polonara, F., 2013. Domestic demand-side management (DSM): Role of heat pumps and thermal energy storage (TES) systems. *Applied Thermal Engineering*, 51(1-2).

Bekele, G. & Tadesse, G., 2012. Feasibility study of small Hydro/PV/Wind hybrid system for off-grid rural electrification in Ethiopia. *Applied Energy*, 97(0), pp.5–15. Available at: http://www.sciencedirect.com/science/article/pii/S0306261911007653.

Biviji, M.A. et al., 2012. Price elasticity of electricity demand for various dynamic rate programs. *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, p.1.

BRE, 2008. *Final Report: The impact of changing energy use patterns in buildings on peak electricity demand in the UK*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48191/3150-final-report-changing-energy-use.pdf.

Clarke, J.C. et al., 2013. Electricity storage within the domestic sector as a means to enable renewable energy integration within existing electricity networks. In *13th Conf. Int. Building Performance Simulation Association, Chambery, France*.

DECC, 2014. *Energy Consumption in the UK (2014) - Chapter 3: Domestic energy consumption in the UK between 1970 and 2013*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/338662/ecuk_chapter_3_domestic_factsheet.pdf.

DECC, 2013. *Quarterly Energy Prices: June 2013*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/208286/qep_june_2013.pdf.

DECC & BRE, 2014. *Energy Follow-Up Survey 2011 - Report 9: Domestic appliances, cooking and cooling equipment*, Available at:

https://www.gov.uk/government/statistics/energy-follow-up-survey-efus-2011.

Doostizadeh, M. & Ghasemi, H., 2012. A day-ahead electricity pricing model based on smart metering and demand-side management. *Energy*, 46(1), pp.221–230. Available at: http://www.sciencedirect.com/science/article/pii/S0360544212006603.

Dorji, T., Urmee, T. & Jennings, P., 2012. Options for off-grid electrification in the Kingdom of Bhutan. *Renewable Energy*, 45(0), pp.51–58. Available at: http://www.sciencedirect.com/science/article/pii/S0960148112001504.

Farret, F.A. & Simões, M.G., 2006. Micropower System Modelling with Homer. In *Integration of Alternative Sources of Energy*. Wiley-IEEE Press, pp. 379–418.

Faruqui, A., Hledik, R. & Tsoukalis, J., 2009. The Power of Dynamic Pricing. *The Electricity Journal*, 22(3), pp.42–56. Available at: http://www.sciencedirect.com/science/article/pii/S1040619009000414 [Accessed September 3, 2014].

Filippini, M., 1995. Electricity demand by time of use An application of the household AIDS model. *Energy Economics*, 17(3), pp.197–204. Available at: http://www.sciencedirect.com/science/article/pii/014098839500017O [Accessed February 5, 2014].

Flett, G.H. & Kelly, N., 2015. Household-differentiated demand modelling for communities. In *BS2015, 14th International Conference of the IBPSA*. Available at: http://strathprints.strath.ac.uk/54518/1/Flett_Kelly_BS2015_Household_differentiated_demand_modelling_for_communities.pdf.

Flett, G.H. & Kelly, N., 2014. Towards detailed occupancy and demand modelling of low-carbon communities. In *1st International Conference on Zero Carbon Buildings Today and in the Future, ZCB2014,*.

Gower, T.L., 2013. *2011 Census Analysis-Comparing Rural and Urban Areas of England and Wales*, Available at: http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/dcp171776_337939.pdf.

Grandjean, A., Adnot, J. & Binet, G., 2012. A review and an analysis of the residential electric load curve models. *Renewable and Sustainable Energy Reviews*, 16(9), pp.6539–6565. Available at: http://www.sciencedirect.com/science/article/pii/S1364032112004820 [Accessed June 1, 2016].

Hafez, O. & Bhattacharya, K., 2012. Optimal planning and design of a renewable energy based supply system for microgrids. *Renewable Energy*, 45(0), pp.7–15. Available at: http://www.sciencedirect.com/science/article/pii/S0960148112000985.

Homer Energy, 2012. HOMER. Available at: http://homerenergy.com/.

Intertek, 2012. *Household Electricity Survey - A study of domestic electrical product usage*, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/208097/10043_R66141HouseholdElectricitySurveyFinalReportissue4.pdf.

Lijesen, M.G., 2007. The real-time price elasticity of electricity. *Energy Economics*, 29(2), pp.249–258. Available at: http://www.sciencedirect.com/science/article/pii/S0140988306001010.

Mendes, G., Ioakimidis, C. & Ferrao, P., 2011. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. *Renewable and Sustainable Energy Reviews*.

Newsham, G.R. & Bowker, B.G., 2010. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, 38(7), pp.3289–3296. Available at: http://www.sciencedirect.com/science/article/pii/S0301421510000510 [Accessed July 28, 2014].

Office for National Statistics, 2013. *Population and Household Estimates for the United Kingdom, March 2011*, Available at: http://www.ons.gov.uk/ons/dcp171778_304116.pdf.

Office for National Statistics, 2003. *The United Kingdom 2000 Time Use Survey*,

Pipattanasomporn, M. et al., 2014. Load profiles of selected major household appliances and their demand response opportunities. *IEEE Transactions on Smart Grid*, 5(2), pp.742–750.

Prodromidis, G.N. & Coutelieris, F.A., 2010. A comparative feasibility study of stand-alone and grid connected RES-based systems in several Greek Islands. *Renewable Energy*, 36(7), pp.1957–1963. Available at: http://www.sciencedirect.com/science/article/pii/S0960148110005756.

Prodromidis, G.N. & Coutelieris, F.A., 2012. Simulations of economical and technical feasibility of battery and flywheel hybrid energy storage systems in autonomous projects. *Renewable Energy*, 39(1), pp.149–153. Available at: http://www.sciencedirect.com/science/article/pii/S096014811100437X.

Richardson, I. et al., 2010. Domestic electricity use: A high-resolution energy demand model. *Energy and Buildings*, 42(10), pp.1878–1887. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0378778810001854 [Accessed January 31, 2013].

Richardson, I., Thomson, M. & Infield, D., 2008. A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings*, 40(8), pp.1560–1566. Available at: http://www.sciencedirect.com/science/article/pii/S0378778808000467.

Sargent, R.G., 1981. *An assessment procedure and a set of criteria for use in the evaluation of computerized models and computer-based modeling tools*, Syracuse, NY: SYRACUSE UNIV N Y DEPT OF INDUSTRIAL ENGINEERING AND OPERATIONS RESEARCH.

Sargent, R.G., 2005. Verification and validation of simulation models. In *Proceedings of the 2005 Winter Simulation Conference*. pp. 130–143. Available at: http://delivery.acm.org/10.1145/1170000/1162736/p130-sargent.pdf?ip=130.159.200.13&acc=ACTIVE SERVICE&key=C2716FEBFA981EF1A6C31C7A1C92E751D66EF845E17AF165&CFID=221655955&CFTOKEN=97182266&__acm__=1370270426_25688848375cc5ef5ebdb94713634977.

Spees, K. & Lave, L.B., 2007. Demand Response and Electricity Market Efficiency. *The Electricity Journal*, 20(3), pp.69–85. Available at: http://www.sciencedirect.com/science/article/pii/S1040619007000188 [Accessed November 28, 2014].

Swan, L.G. & Ugursal, V.I., 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and*

Sustainable Energy Reviews, 13(8), pp.1819–1835. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1364032108001949 [Accessed March 4, 2013].

Torriti, J., 2014. A review of time use models of residential electricity demand. *Renewable and Sustainable Energy Reviews*, 37, pp.265–272. Available at: http://www.sciencedirect.com/science/article/pii/S1364032114003591 [Accessed February 18, 2016].

Tracey, B. & Wallach, J., 2003. *Peak-Shaving/Demand Response Analysis: Load-Shifting by Residential Customers*, Available at: http://sedc-coalition.eu/wp-content/uploads/2011/05/Tracey-Load-Shifting-by-Residential-Customers-2003.pdf.

Widén, J. & Wäckelgård, E., 2010. A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87(6), pp.1880–1892. Available at: http://www.sciencedirect.com/science/article/pii/S0306261909004930 [Accessed December 25, 2015].

Wilke, U., 2013. *Probabilistic bottom-up modelling of occupancy and activities to predict electricity demand in residential buildings*. ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE.

Yohanis, Y.G. et al., 2008. Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. *Energy and Buildings*, 40(6), pp.1053–1059. Available at: http://www.sciencedirect.com/science/article/pii/S037877880700223X [Accessed March 3, 2015].

Chapter 7: Simulation Results and Discussion

7.1 Impact and Performance Indicators

Before the results analysis process can begin and meaningful conclusions drawn, it is first necessary to identify the metrics and indicators which can be used to gauge the performance of the variable energy pricing strategies included in the modelling. Doing so provides a means of judging the impact of variable pricing and comparing the impact and performance of each of the developed strategies.

The selected indicators must convey the various impacts of variable pricing in as simple and as clear a way as possible. In order to select an appropriate set of performance indicators, we must consider what it is that we wish to learn from the results data, namely:

1. Does the introduction of variable pricing result in DR, and if so, how much?
2. What impact does variable energy pricing have on household energy bills and consumption patterns?
3. How does the impact on different households vary according to key characteristics?

The selection of relevant indicators and metrics must therefore be done with a view to answering these questions in a clear and concise way. This task can be usefully simplified by considering the results analysis from two separate viewpoints: the community level and the household level.

7.1.1 Statistical indicator selection

At the most basic level, the aim of the variable pricing strategies - and the goal of DR in this context - is to improve the match between the energy demand profiles of the community and the RES profiles associated with the renewable supply technologies featured in the SAHES (henceforth referred to as the demand-RES match). Quantifying this match (and in particular, changes to it) is therefore the primary aim of the results analysis. The selected metrics and statistical indicators must therefore be capable of quantifying and comparing the DR achieved in each of the modelled scenarios.

There are numerous metrics which can potentially be used to quantify the demand-RES match, including:

- Shared/residual area
- Least squares method
- Coefficient of Variation of the Root Mean Square Error
- Pearson's Product Moment Correlation Coefficient
- Spearman's Rank Correlation Coefficient
- Inequality Coefficient

The comparison of different demand profiles and RES profiles across different scenarios requires metrics which facilitate the direct comparison of results, even under different demand and RES scenarios. The calculation of shared and residual area as an indicator of demand-RES match appears suitable, as they quantify the amount of demand met by RES, the remaining deficit and any resulting surplus, which has obvious implications regarding back-up generation and energy storage requirements. However, while potentially useful, none of these measures convey the extent of the demand-RES match. In addition, the need to prioritise either deficit, surplus or the amount of demand met would make comparing such results difficult (Born, 2001).

The use of the least squares method is also considered unsuitable. While this can be used to directly compare the match between profiles where one profile is common i.e. the demand-RES match both before and after the introduction of DR in any given scenario, it does not facilitate such a comparison across differing scenarios, due to the lack of an upper limit.

The same limitations could apply to the use of Root Mean Square Error (RMSE), which represents the sample standard deviation between two sets of time series data by aggregating the magnitude of variation between the datasets. Lower values indicate less variation between profiles, and therefore a closer match. The formula for calculating RMSE in this context is shown in Equation 3.

$$\mathrm{RMSE}_{d:RES} = \sqrt{\frac{\sum_{t=1}^{n}(S_t - D_t)^2}{n}} \tag{3}$$

where: S_t and D_t are the RES and community-wide demand values respectively, and n is the number of data points in both datasets (in this case 24).

The lack of an upper limit to RMSE values makes comparing results across different scenarios challenging. This can, however, be overcome by normalising values. There is no single method of normalisation for RMSE values which is used consistently, with the range and mean value of observed data used most frequently. In this instance normalisation is achieved by dividing the RMSE value by the mean demand value, as shown in Equation 4. This normalised value is referred to as the Coefficient of Variation of the Root Mean Square Error (CV(RMSE)).

$$CV(RMSE)_{d:RES} = \frac{RMSE_{d:RES}}{\overline{D}} \tag{4}$$

where $\overline{D}$ is the mean value of the original demand profile.

The Pearson product moment correlation coefficient ($r_{\mathrm{d:RES}}$) is a simple measure of the linear correlation between two variables. The formula for calculating the $r_{\mathrm{d:RES}}$ value in this context is shown in Equation 5. Potential $r_{\mathrm{d:RES}}$ values range from 1, which indicates a perfect positive correlation, to -1, which indicates a perfect negative correlation.

$$r_{d:RES} = \frac{\sum_{t=1}^{n}(D_t - \overline{D}).(S_t - \bar{S})}{\sqrt{\sum_{t=1}^{n}(D_t - \overline{D})^2}\ .\sqrt{\sum_{t=1}^{n}(S_t - \bar{S})^2}} \tag{5}$$

where D_t is the community-wide energy demand at time t, S_t is the total RES at time t, d is the average demand over the time period n, s is the average RES over time period n, and $\overline{D}$ and $\bar{S}$ are the mean demand and supply values, respectively.

Like the Pearson product moment correlation coefficient, Spearman's Rank Correlation Coefficient ($\rho_{\mathrm{d:RES}}$) will always result in a value between -1 and 1, making it suitable for direct comparison, with a value of -1 describing a perfect negative correlation and 1 a perfect positive correlation. The $\rho_{\mathrm{d:RES}}$ value also accounts for the correlation in the shape of demand and RES curves, and does not account for magnitudinal variation. The equation for calculating $\rho_{\mathrm{d:RES}}$ is shown in Equation 6.

$$\rho_{d:RES} = \frac{\sum_{t=1}^{n}(D_t - d).(S_t - s)}{\sqrt{\sum_{t=1}^{n}(D_t - d)^2} \cdot \sqrt{\sum_{t=1}^{n}(S_t - s)^2}} \tag{6}$$

where D_t is the community-wide energy demand at time t, S_t is the total RES at time t, d is the average demand over the time period n, and s is the average RES over time period n.

The Inequality Coefficient (IC) is a measure of inequality in time series data caused by unequal tendency (mean), unequal variation (variance) and imperfect co-variation (co-variance). Values range between 0 and 1, with 0 indicating a perfect match, and 1 indicating no match whatsoever. This is shown below in Equation 7.

$$IC_{d:RES} = \frac{\sqrt{\frac{1}{n}.\sum_{t=1}^{n}(D_t - S_t)^2}}{\sqrt{\frac{1}{n}.\sum_{t=1}^{n}(D_t)^2} + \sqrt{\frac{1}{n}.\sum_{t=1}^{n}(S_t)^2}} \tag{7}$$

where D_t is the community-wide energy demand at time t, S_t is the total RES at time t, d is the average demand over the time period n, and s is the average RES over time period n.

In order to clearly identify which of the above measures are best suited to this study, they were subjected to a number of statistical tests. This involved the application of $CV(RMSE)_{d:RES}$, $r_{d:RES}$, $\rho_{d:RES}$ and $IC_{d:RES}$ to a pair of results samples taken from the modelled scenarios:

1) Minimum RES conditions, under VToU pricing strategy, during summer.
2) Maximum RES conditions, under the RTP pricing strategy, during winter.

These scenarios were selected as they represent a broad range of RES conditions, as well as including the effect of two different variable pricing strategies and seasonal variation. The RES profiles and the demand profiles (both before (D1) and after (D2) the application of the corresponding pricing strategy) for scenarios 1 and 2 are shown in Figure 7-1 and Figure 7-2 respectively.

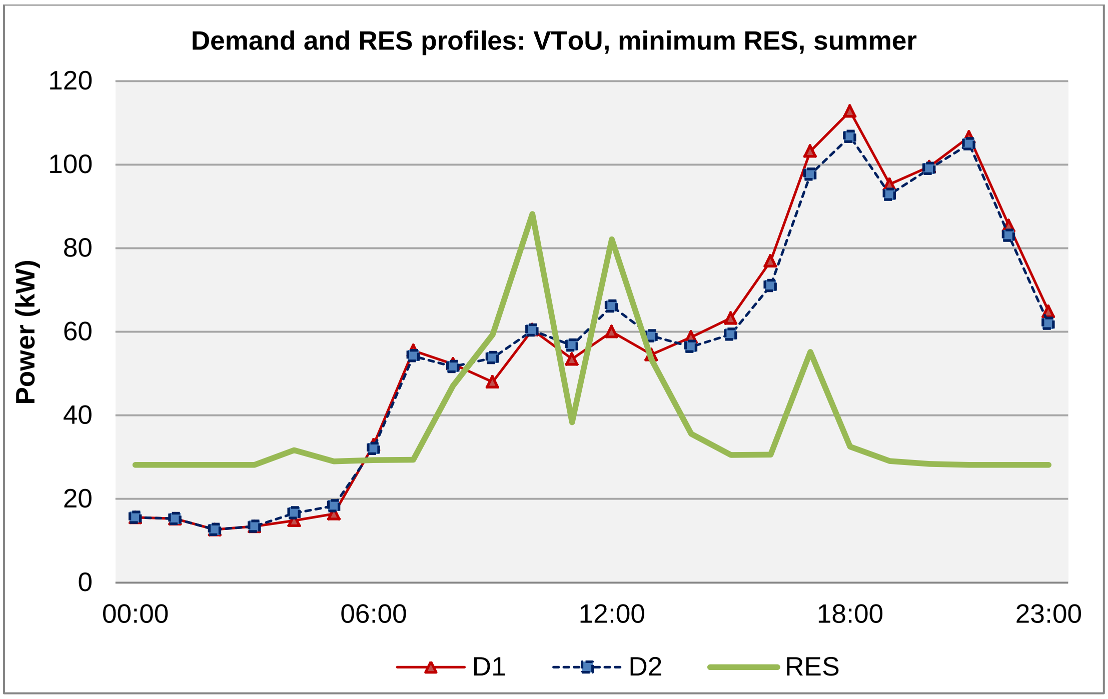


Figure 7-1 - RES and demand profiles used in statistical indicator test scenario 1.

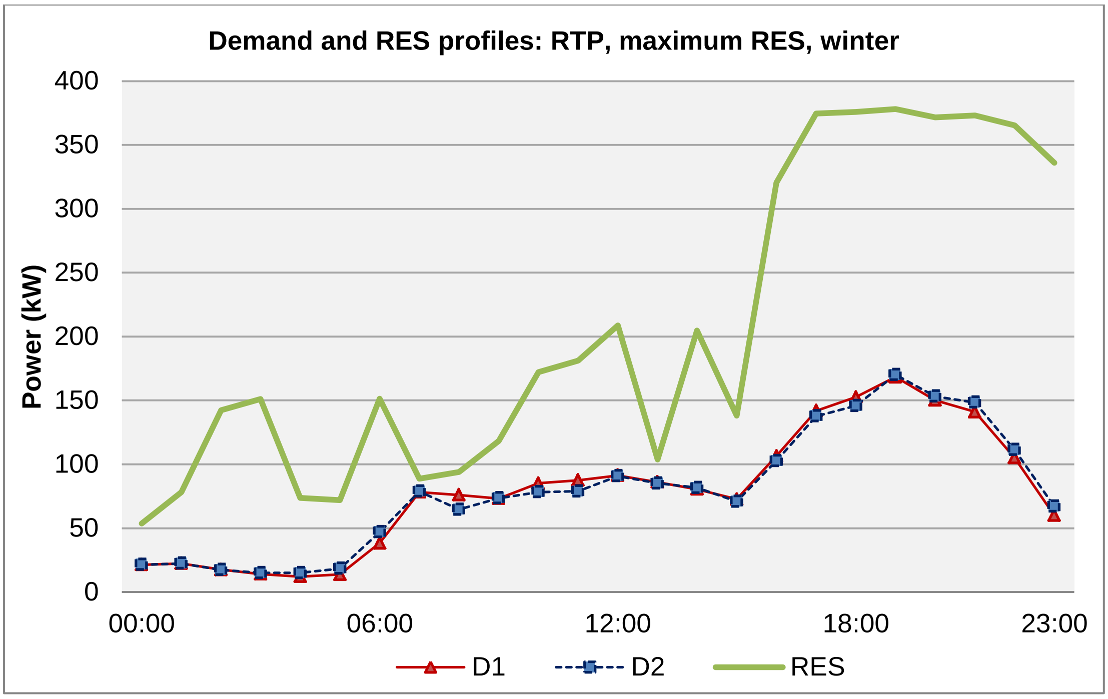


Figure 7-2 - RES and demand profiles used in statistical indicator test scenario 2.

All four of the statistical measures included in the analysis were applied to both scenarios, and the values for the demand-RES match both before and after the application of the variable pricing strategy in question were recorded. Comparing the change in values which occurs across both demand scenarios helps identify which of the statistical measures is most sensitive to change, and is therefore most appropriate for use in this context.

Table 7-1 and Table 7-2 show the resulting values for the four statistical indicators included in the test, under both scenarios. All four indicators show an improvement in the demand-RES match in both scenarios. This is more pronounced in the first scenario, where the changes to demand levels are larger in scale relative to the corresponding RES profile.

Table 7-1 - Results of the statistical indicator test for scenario 1.

	D1	D2	Δ	%Δ
$CV(RMSE)_{d:RES}$	0.680	0.644	-0.037	-5.4%
$r_{d:RES}$	0.099	0.150	0.051	51.4%
$\rho_{d:RES}$	0.252	0.304	0.052	20.7%
$IC_{d:RES}$	0.137	0.131	-0.006	-4.4%

Table 7-2 - Results of the statistical indicator test for scenario 2.

	D1	D2	Δ	%Δ
$CV(RMSE)_{d:RES}$	1.920	1.911	-0.009	-0.48%
$r_{d:RES}$	0.817	0.843	0.026	3.2%
$\rho_{d:RES}$	0.821	0.800	-0.021	-2.5%
$IC_{d:RES}$	0.392	0.390	-0.002	-0.46%

The results show the $r_{d:RES}$ value to be the most sensitive to the small changes in the demand-RES relationship, followed by $\rho_{d:RES}$. This suggests that the Pearson product moment coefficient is the best suited to quantify the demand-RES match, and the changes which result from the introduction of variable pricing.

However, while the $r_{d:RES}$ value has been shown to provide a useful indication of changes in the *shape* of demand profiles resulting from DR, the use of correlation coefficients alone cannot be deemed sufficient for the analysis of DR. This is primarily due to the inability of such metrics to fully account for changes in demand which are more uniform i.e. extend across several hours or a whole day, and therefore have a significant impact on RES surplus/deficit levels. With this in mind, a third test scenario was introduced, in which the demand profiles in question varied only magnitudinally i.e. the shape of the demand profiles remained the same. The RES and original community demand profile (D1) from scenario 1 (VToU, during minimum RES in summer) were used, with two additional demand profiles (D2 and D3) generated by applying a blanket increase/decrease of 10kW respectively, across all timesteps. The resulting profiles are shown in Figure 7-3.

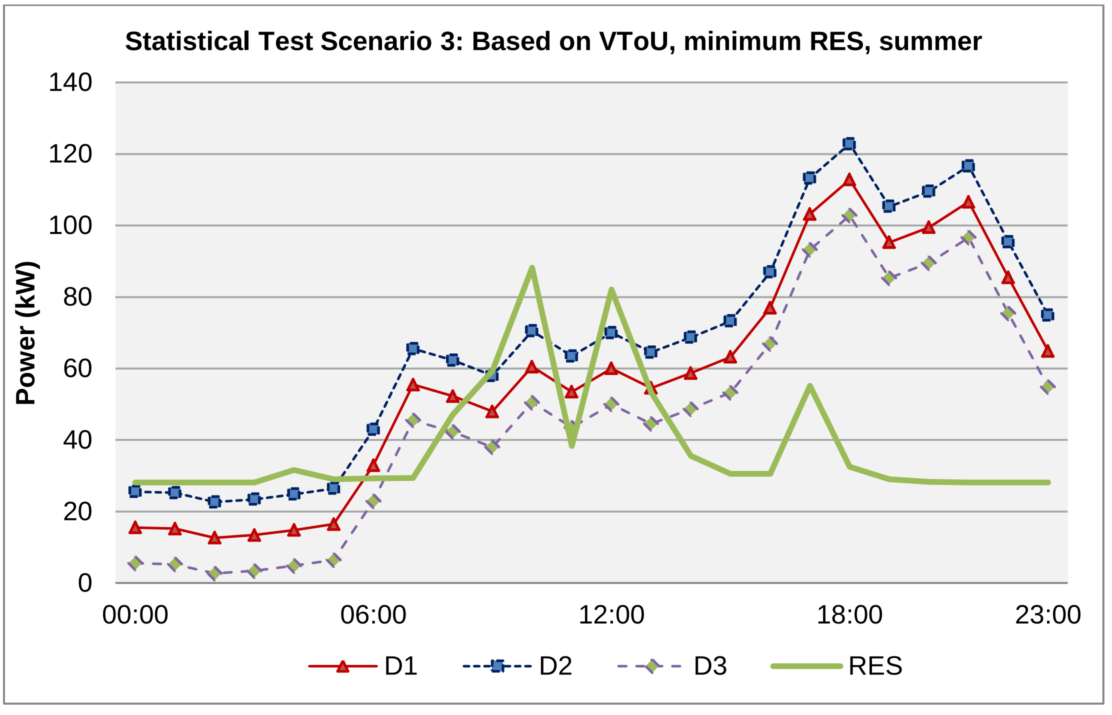


Figure 7-3 - RES and demand profiles used in statistical indicator test scenario 3.

This test allowed the sensitivity to magnitudinal variation of each of the metrics to be compared. The resulting values are shown in Table 7-3.

This third statistical test suggests that without the inclusion of an additional DR indicator to account for changes in the magnitude of demand, there is considerable potential for DR to be under-represent in instances where changes in demand are more uniform, since both correlation coefficient metrics ($r_{d:RES}$ and $\rho_{d:RES}$) fail to account for uniform variation in time-series data. This means that they fail to account for the obvious changes in RES surplus/deficit between the demand scenarios - a value of particular significance in SAHES.

Table 7-3- Results of the statistical indicator test for scenario 3.

	D1	D2	D3
CV(RMSE) $_{d:RES}$	0.680	0.663	0.747
$r_{d:RES}$	0.099	0.099	0.099
$\rho_{r:RES}$	0.252	0.252	0.252
IC $_{d:RES}$	0.083	0.086	0.084

Interestingly, the remaining two metrics, CV(RMSE)$_{d:RES}$ and IC$_{d:RES}$, come to differing conclusions regarding which of the three demand profiles is best matched to the RES profile. While the CV(RMSE)$_{d:RES}$ values show D3 to be the best match with RES, the IC$_{d:RES}$ values suggest that D1 achieves the best match. In order to distinguish which of these conflicting results best suits the needs of this project, it is necessary to re-consider the basis for the inclusion of a secondary DR metric: the need to account for changes in the *quantity* of RES surplus/deficit which results from DR. Given the emphasis placed on magnitudinal differences in the calculation of CV(RMSE) $_{d:RES}$, it was selected over IC $_{d:RES}$ as the preferred metric, and will be used along with the other community level indicators discussed below.

7.1.2 Community level impacts

Viewing the results at a community level allows the overall impact of each of the pricing strategies under the various scenarios to be assessed. In any real-world application, these results would likely provide a basis from which to evaluate the impact of variable energy pricing at the system-wide scale.

At a community level, the focus of the results analysis is placed on the impact of variable pricing on the operation of the SAHES as a whole. This includes the demand-RES match as discussed in the previous section, but also includes additional indicators which can also be used to quantify and analyse the impact of the introduction of variable energy pricing. These additional metrics provide additional information about the DR achieved in each of the modelled scenarios, thereby creating a more in-depth understanding of the results.

As well as quantifying the demand-RES match ($r_{d:RES}$) which occurs at a community level, the Pearson product moment correlation coefficient can also be used to quantify the match between community demand before and after the introduction of variable pricing. This value, referred to as r_d, can be used to gauge the extent of community wide DR, and is calculated using Equation 8.

$$r_d = \frac{\sum_{t=1}^{n}\left(D_{1_t} - \overline{D_1}\right).\left(D_{2_t} - \overline{D_2}\right)}{\sqrt{\sum_{t=1}^{n}\left(D_{1_t} - \overline{D_1}\right)^2} \, . \sqrt{\sum_{t=1}^{n}\left(D_{2_t} - \overline{D_2}\right)^2}} \quad (8)$$

where D_{1_t} is the original energy demand during timestep *t*, D_{2_t} is the new energy demand (under variable pricing) during timestep *t*, $\overline{D_1}$ is the average original demand over the total number of timesteps *n* and $\overline{D_2}$ is the average new energy demand over the total number of timesteps *n*.

Whilst this metric provides an indication of the extent of the DR undertaken by the community as a whole, it should be noted that this value can be skewed by a small number of highly responsive households, and should not therefore be confused with overall levels of engagement.

The r_d metric can also be used to help quantify the extent to which the individual households within the community engage in DR. By applying Equation 3 at the household level, it is possible to identify which households engaged in DR and which didn't, since any individual DR action will result in a change in a household's r_d value (excluding the highly unlikely case of a perfectly uniform increase/decrease in demand across a 24 hour period). Those households with an r_d value of 1.000 can therefore be deemed unresponsive i.e. they did not engage in DR. This is referred to as the community DR engagement rate, and is expressed as a percentage of the total number of households.

The use of CV(RMSE) $_{d:RES}$ (as described in the previous section) can be supplemented by comparing the hourly demand levels before and after the introduction of variable energy pricing, thereby highlighting the number of hours during which DR was engaged in. This value, referred to as the number of responsive hours, shall therefore be used in the results analysis as another means of comparing the DR which results from the introduction of variable energy pricing.

The change in the daily peak demand caused by DR was also included in the analysis. Despite not being the primary focus of variable pricing in this context (as discussed in Chapter 4) peak demand reduction can still be considered to be of interest due to its relevance to the sizing of energy generation components and infrastructure. Therefore it is also included in the analysis.

7.1.3 Household level impacts

Assessing impact at the household level allows for the inter-household comparison of the impacts of variable pricing. This provides further depth to the analysis, and allows any 'winners' and 'losers' to be identified. It also helps establish the extent to which the impacts of variable pricing vary depending on household characteristics. This level of detail is often neglected in studies relating to demand elasticity, with large numbers of consumers often being assigned the same elasticity values. However, such an approach fails to account for the diversity of attitudes towards demand flexibility, thereby neglecting a major aspect of social viability when it comes to variable energy pricing: ensuring that non-responsive consumers are not subject to excessive 'punishment' for their refusal or inability to engage in DR.

As described in the previous chapter, the households featured in the notional SAHES model vary in the number of occupants, their pattern of occupancy, their use of electric heating, and in their elasticity and appliance use grouping. It follows that there is therefore considerable scope for variation in the amount of DR that each household will engage in under each of the modelled scenarios and pricing strategies.

At the household level the focus of the results analysis is on the impacts of variable energy pricing on each household, and the extent to which these impacts vary. Therefore, the performance indicators of interest at this level are:

1. The changes in demand profile which result from exposure to variable energy pricing.
2. The disruption to energy consumption patterns that result from DR.
3. The changes in daily household energy bills that occur under variable energy pricing.
4. The variation in the impacts of variable energy pricing experienced by the different household types.

As discussed in the previous section, the Pearson product moment calculation can be applied at the household level. This is done by calculating the r_d value of household demand profiles before and after the introduction of variable pricing.

Since lower household r_d values are indicative of a greater number/extent of DR actions, they can also be used to indicate the extent to which engaging in DR causes changes to household energy consumption patterns. However, the *disruption* caused by these DR actions is more difficult to quantify. Since DR actions can either be implemented through direct consumer action or by automation technology, two DR actions which have a similar impact on overall household consumption levels could differ dramatically in terms of the disruption they cause to the household's consumption patterns, due solely to the fact that one requires consumer interaction and the other doesn't. The perceived 'transaction cost' to the consumer of carrying out these two identical actions can therefore vary significantly.

Variation in the attitude of consumers towards DR further adds to the difficulties associated with quantifying such disruption, as some consumers are likely to be more sensitive to changes in their consumption patterns than others (this is reflected in the model through the different elasticity bandings used). This means that while one household could regard the disruption caused by a given DR action to be minimal, another household might regard the very same DR action as highly disruptive. Disruptions are also greatly influenced by the overall levels of consumption already present (since a single shifted/curtailed load represents a larger change in a household's overall consumption pattern if that household has a smaller level of daily consumption to begin with). This makes it very difficult to accurately quantify the extent of the disruption caused by each individual DR action. Therefore, given the lack of an accurate and objective metric, the disruption to household energy consumption patterns will not be included in the results analysis.

Another important impact to consider at the household level is the impact of variable energy pricing on daily household energy bills. Due to the use of consumer price elasticity of demand as the basis for DR in the model, households will carry out DR actions which either avoid bill increases or result in bill decreases. Given the lack of other quantifiable social metrics, this is also seen as the primary indicator of socio-economic viability for this study. Again, focus is placed on the percentage change relative to base case conditions rather than the specific bill amount.

7.1.4 Simulation process

The total number of simulations conducted was 36, with each of the 4 seasonal days being simulated under the corresponding minimum, mean and maximum RES conditions, and under each of the 3 variable pricing strategies, as shown in Table 7-4.

Table 7-4 - All 36 of the modelled scenarios.

	VToU			RTP			VCPP		
	Min RES	Mean RES	Max RES	Min RES	Mean RES	Max RES	Min RES	Mean RES	Max RES
Spring	✔	✔	✔	✔	✔	✔	✔	✔	✔
Summer	✔	✔	✔	✔	✔	✔	✔	✔	✔
Autumn	✔	✔	✔	✔	✔	✔	✔	✔	✔
Winter	✔	✔	✔	✔	✔	✔	✔	✔	✔

Input data for these simulations was developed using the process described in chapter 5, with results data being written to separate files for further analysis, with one file for each of the 36 individual simulations. Each results file includes the hourly demand profile for each of the 100 households, as well as each household's original demand profile. In addition, each results file includes a breakdown of the daily bills issued to each consumer, as well as details of the community-wide daily energy demand profile both before and after the introduction of variable pricing. This provides a means of comparing the various results, and forms the basis for the results analysis process.

Following the successful completion of the simulations, the results data were analysed in order to identify resulting outcomes.

7.2 Community Level Results

7.2.1 Impact upon demand-supply match

Increasing the demand-supply match (by increasing the correlation between the demand and RES profiles) is the principle aim of DR in this context. As such, it serves as a useful starting point for assessing the levels of DR achieved under each of the modelled scenarios.

Figure 7-4 to Figure 7-6 show the impact upon $r_{d:RES}$ had by each of the 3 variable pricing strategies under each of the 12 modelled RES conditions, relative to the base case model. These graphs show that all 3 pricing strategies result in changes in the $r_{d:RES}$ value, but to varying extents.

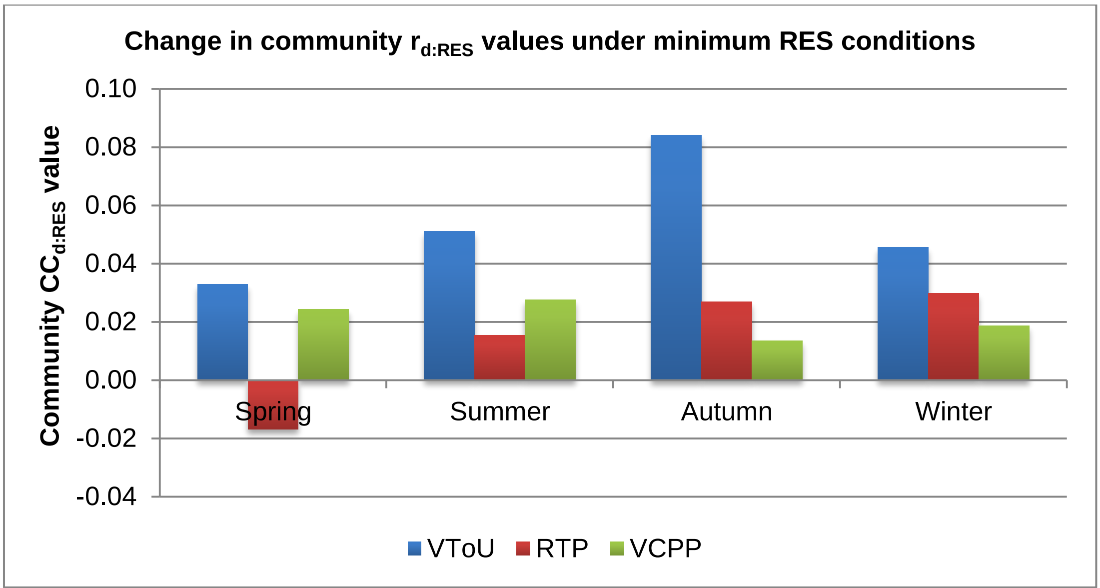


Figure 7-4 - Graph showing the increase in $r_{d:RES}$ achieved under minimum RES conditions.

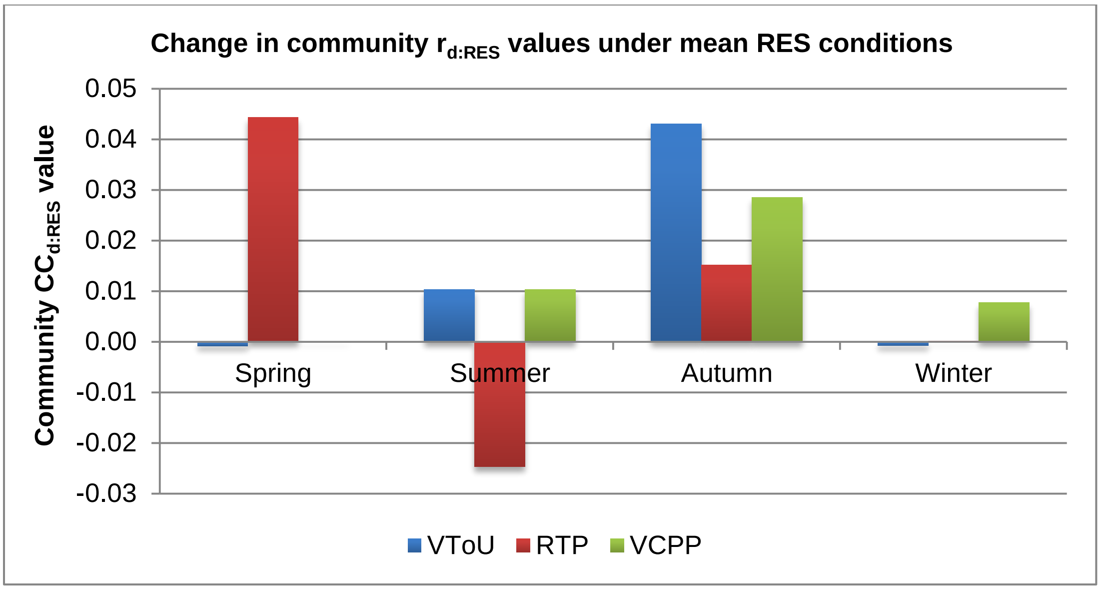


Figure 7-5 - Graph showing the increase in $r_{d:RES}$ achieved under mean RES conditions.

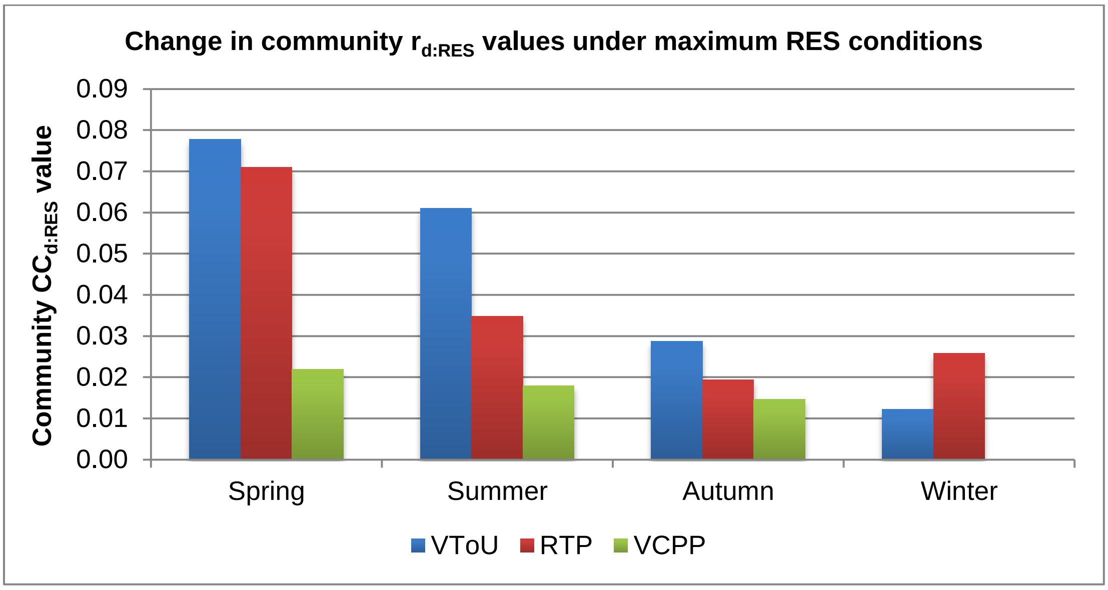


Figure 7-6 - Graph showing the increase in $r_{d:RES}$ achieved under maximum RES conditions.

Results range from a decrease in $r_{d:RES}$ of 0.025 (under RTP during mean RES conditions in Summer) to an increase of 0.084 (under VToU during minimum RES conditions in the autumn seasonal day). Figure 7-7 and Figure 7-8 show the corresponding community demand profiles as well as the corresponding RES profile for each scenario. These graphs provide a visual representation of the range of $r_{d:RES}$ values resulting from the introduction of variable pricing, and the impact of DR upon community consumption levels.

While Figure 7-7 clearly shows a slight reduction in peak demand under variable pricing (RTP in this instance), it is the last hours of the day which cause the decrease in $r_{d:RES}$, since the demand is shown to decrease at a time of RES surplus.

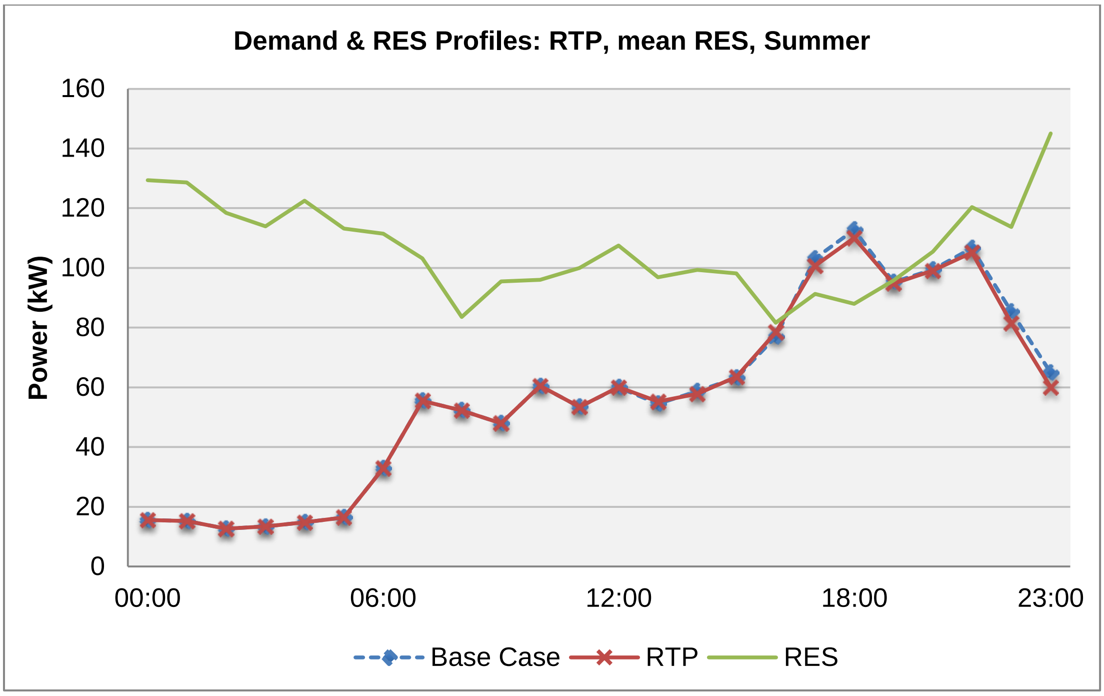


Figure 7-7 - Graph showing demand and RES profiles associated with maximum $r_{d:RES}$ decrease.

In Figure 7-8 - selected as it sees the greatest $r_{d:RES}$ increase across all 36 scenarios - the changes in demand are more in line with the aims of the variable pricing, in that demand decreases significantly during RES surplus and decreases substantially during the times of greatest deficit.

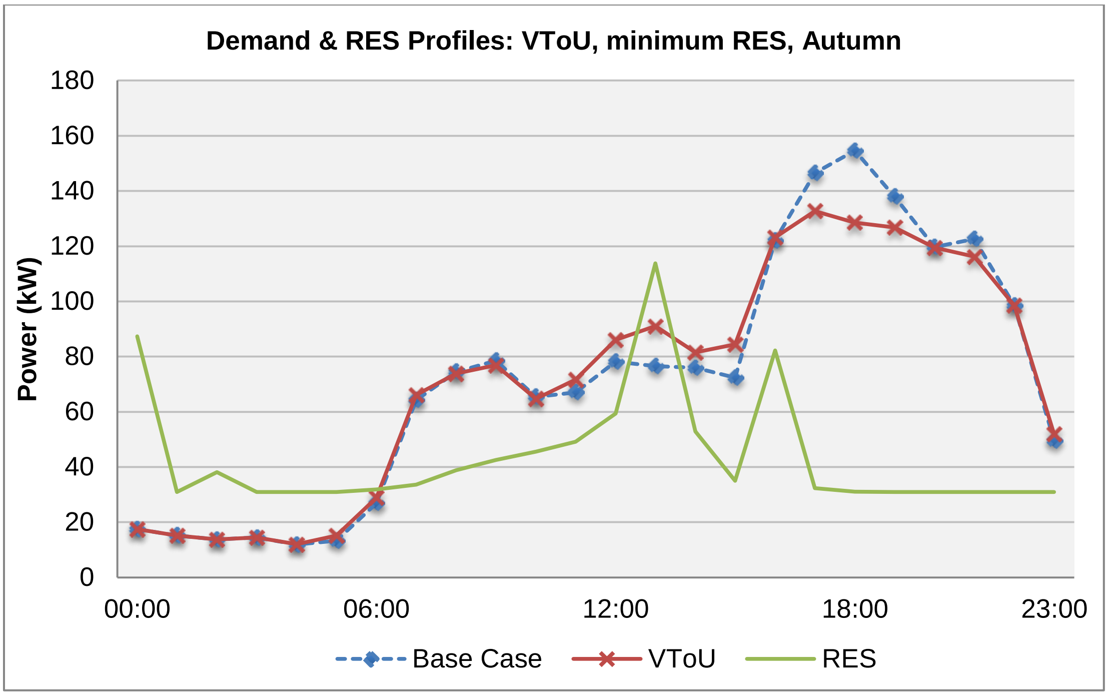


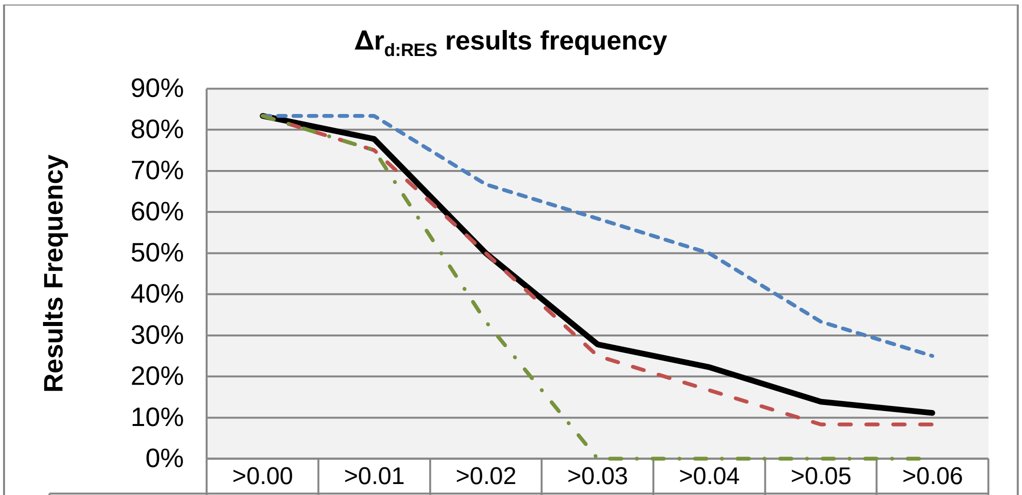
Figure 7-8 - Graph showing demand and RES profiles associated with maximum $r_{d:RES}$ increase.

The results from all 36 of the modelled scenarios are shown in Table 7-5, which shows the change in the demand-RES match which results from the introduction of variable pricing in all of the modelled scenarios. This shows VToU to be the most successful of the three strategies at promoting DR, with an average improvement of 0.037 and a maximum of 0.084. VCPP is the poorest performer, failing to achieve an improvement of more than 0.03 in any of the modelled scenarios, and failing to result in DR during 2 separate scenarios. However, while VCPP does fail to achieve DR in these scenarios, it never results in a negative result i.e. a decrease in $r_{d:RES}$, unlike RTP and VToU, both of which do so on 2 occasions.

Table 7-5 - The change in $r_{d:RES}$ achieved in each of the modelled scenarios.

		Variable Pricing Strategy		
Scenario		VToU	RTP	VCPP
Winter	Min RES	0.046	0.030	0.019
	Mean RES	-0.001	0.000	0.008
	Max RES	0.012	0.026	0.000
Spring	Min RES	0.033	-0.017	0.024
	Mean RES	-0.001	0.044	0.000
	Max RES	0.078	0.071	0.022
Summer	Min RES	0.051	0.015	0.028
	Mean RES	0.010	-0.025	0.010
	Max RES	0.061	0.035	0.018
Autumn	Min RES	0.084	0.027	0.013
	Mean RES	0.043	0.015	0.029
	Max RES	0.029	0.019	0.015
	Average	*0.037*	*0.020*	*0.015*
	Min	*-0.001*	*-0.025*	*0.000*
	Max	*0.084*	*0.071*	*0.029*

Figure 7-9 shows the frequency with which each pricing strategy results in changes in $r_{d:RES}$ of varying magnitude (and therefore significance). Despite the small sample sizes - just 12 scenarios for each individual pricing strategy - the results are informative when it comes to determining the comparative significance of the levels of DR achieved by each variable pricing strategy. Again, VToU outperforms both RTP and VCPP, with 25% of all modelled scenarios resulting in a change in $r_{d:RES}$ of more than 0.06, and two thirds resulting in a change of at least 0.02. In all instances where a positive result is achieved i.e. a change in $r_{d:RES}$, the resulting change is greater than 0.01.



	>0.00	>0.01	>0.02	>0.03	>0.04	>0.05	>0.06
All	83%	78%	50%	28%	22%	14%	11%
VToU	83%	83%	67%	58%	50%	33%	25%
RTP	83%	75%	50%	25%	17%	8%	8%
VCPP	83%	75%	33%	0%	0%	0%	0%

Figure 7-9 - Graph showing the distribution of the $\Delta r_{d:RES}$ results.

The significance of the resulting changes in $r_{d:RES}$ values cannot easily be translated into likely implications for real-world applications. Indeed, of the metrics included in the results analysis, changes in $CV(RMSE)_{d:RES}$ and peak demand are likely to have more impact on the sizing of SAHES components. However, these results do suggest that VToU is the most capable of the three pricing strategies to achieve significant changes to the demand-RES match.

As discussed previously, *r* values can under-represent the DR which occurs from more uniform changes in demand i.e. changes which alter the quantity of energy consumed rather than the shape of the demand profile. To account for this, and to provide a more detailed level of analysis, $CV(RMSE)_{d:RES}$ values were also calculated for each modelled scenario. Of particular interest therefore, are scenarios in which the $CV(RMSE)_{d:RES}$ values and $r_{d:RES}$ values present apparently contradictory results regarding the extent of the DR achieved. By comparing these two metrics, it is possible to identify which scenarios resulted in a more consistent, or 'blanket' application of DR, and which scenarios saw DR engaged in during very limited periods.

In order to compare the two metrics and identify such instances, the change in r_{dRES} values ($\Delta r_{d:RES}$) which occurs in each of the 36 modelled scenarios was recorded, and the resulting values ranked (from 1 to 36), so as to identify which scenarios saw the greatest and smallest changes in each metric. This process was repeated for $CV(RMSE)_{d:RES}$ values. When the rankings for the two metrics were compared, the resulting differences were used to identify the scenarios in which the $\Delta r_{d:RES}$ and $CV(RMSE)_{d:RES}$ values vary the most. The results of this comparison are shown in

Table 7-6.

Table 7-6 - Comparison of scenario rankings according to r_{dRES} and $CV(RMSE)_{dRES}$ metrics.

Pricing Strategy	Seasonal Day	RES conditions	Rank: $\Delta r_{d:RES}$	Rank: $\Delta CV(RMSE)_{d:RES}$	Rank: Diff. in ranking
VToU	Spring	Max	2	32	*30*
VToU	Summer	Max	4	33	*29*
VCPP	Autumn	Min	27	5	*22*
RTP	Spring	Max	3	25	*22*
RTP	Winter	Mean	34	15	*19*
RTP	Spring	Mean	7	24	*17*
VToU	Autumn	Max	12	27	*15*
VToU	Spring	Mean	32	19	*13*
RTP	Autumn	Min	15	3	*12*
VCPP	Winter	Mean	31	20	*11*
VCPP	Winter	Min	21	11	*10*
VCPP	Spring	Max	19	28	*9*
RTP	Autumn	Max	20	13	*7*
VCPP	Autumn	Mean	13	6	*7*
VToU	Spring	Min	10	4	*6*
RTP	Spring	Min	23	17	*6*
RTP	Winter	Max	16	22	*6*
VCPP	Autumn	Max	26	21	*5*
VToU	Summer	Mean	29	34	*5*
VToU	Winter	Min	6	2	*4*
VCPP	Summer	Max	22	18	*4*
VToU	Winter	Mean	33	30	*3*
RTP	Summer	Mean	17	14	*3*
VToU	Summer	Min	5	8	*3*
RTP	Winter	Min	11	9	*2*
RTP	Autumn	Mean	25	23	*2*
VCPP	Spring	Min	18	16	*2*
VCPP	Summer	Min	14	12	*2*
RTP	Summer	Min	24	26	*2*
VToU	Autumn	Mean	8	7	*1*
VToU	Winter	Max	28	29	*1*
RTP	Summer	Max	9	10	*1*
VCPP	Summer	Mean	30	31	*1*
VToU	Autumn	Min	1	1	*0*
VCPP	Winter	Max	35	35	*0*
VCPP	Spring	Mean	35	35	*0*

The results vary significantly, with some scenarios having significant differences in the two metric rankings, and some having none. Of most relevance are the instances where the greatest discrepancy in rankings occurs. Under the VToU pricing strategy, during maximum RES conditions in Spring, the changes in $r_{d:RES}$ is ranked 2nd of all the 36 scenarios, while the change in CV(RMSE)$_{d:RES}$ is ranked 32nd. This suggests a comparatively significant change in shape that results in minimal changes to RES surplus/deficit levels, as shown in Figure 7-10.

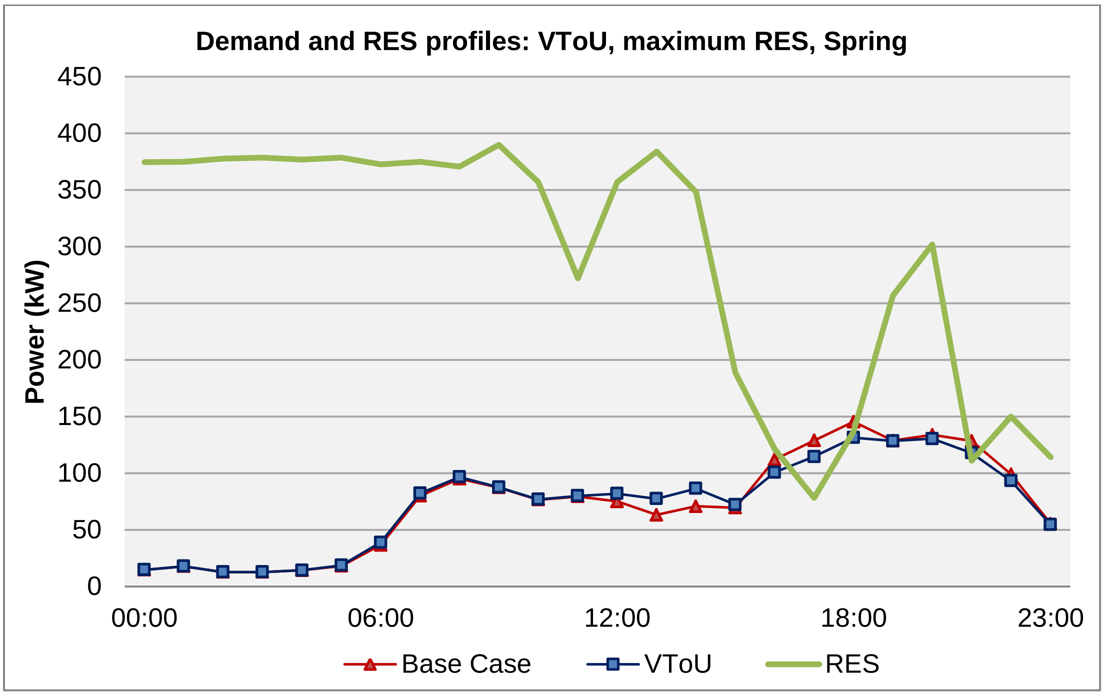


Figure 7-10 - Graph showing demand and RES profiles associated with a small CV(RMSE)$_{d:RES}$ variation but a large $r_{d:RES}$ variation.

In this instance, increases in demand during times of RES surplus (occurring during the early afternoon) and decreases in demand (during the late afternoon) result in a clear change in the shape of the demand profile, but effectively cancel each other out when it comes to measuring change in CV(RMSE)$_{d:RES}$.

Conversely, under the VCPP pricing strategy, during minimum RES conditions in Autumn, the change in CV(RMSE)$_{d:RES}$ is ranked among the highest (5th) and the change in $r_{d:RES}$ value among the lowest (27th). As shown in Figure 7-11, this indicates a substantial change in RES surplus/deficit figures, but with very little change in the shape of the demand profile.

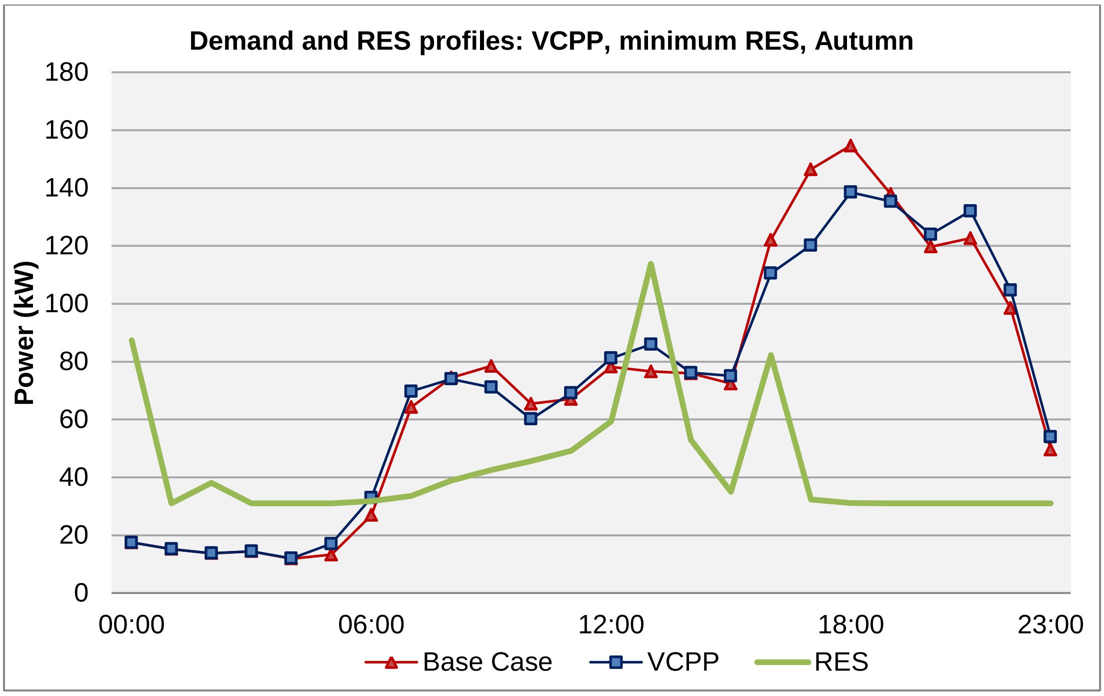
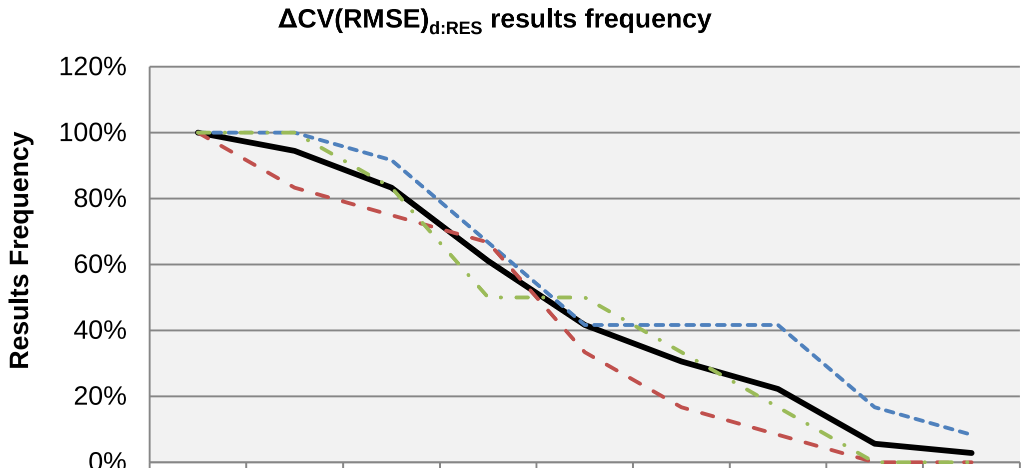


Figure 7-11 - Graph showing demand and RES profiles associated with a large CV(RMSE)$_{d:RES}$ variation but a small r$_{d:RES}$ variation.

These instances show that by including CV(RMSE)$_{d:RES}$ in the results analysis, all aspects of change in demand can be identified and accurately quantified.

Figure 7-12 shows that just as with the r$_{d:RES}$ analysis, plotting the change in CV(RMSE)$_{d:RES}$ values which occurs under each pricing strategy shows VToU to be the most effective of the three pricing strategies. However, while VCPP was the poorest performer when it comes to achieving changes in r$_{d:RES}$, it is RTP which can be seen as the worst of the three in this instance. This is largely due to the fact that is sees the biggest *increase* in CV(RMSE)$_{d:RES}$, with the reductions of more than 0.02 achieved just twice, compared to 4 times under VCPP and 5 times under VToU.



	<0.03	<0.02	<0.01	<0	<-0.01	<-0.02	<-0.03	<-0.04	<-0.05
All	100%	94%	83%	61%	42%	31%	22%	6%	3%
VToU	100%	100%	92%	67%	42%	42%	42%	17%	8%
RTP	100%	83%	75%	67%	33%	17%	8%	0%	0%
VCPP	100%	100%	83%	50%	50%	33%	17%	0%	0%

Figure 7-12 - Graph showing the distribution of the $\Delta CV(RMSE)_{d:RES}$ results.

As discussed above, changes in $CV(RMSE)_{d:RES}$ are likely to have more clearly transferrable implications when it comes to real-world SAHES applications, with significant reductions having a direct bearing on the need for back-up generation and/or on-site energy storage. As such, non-normalised $RMSE_{d:RES}$ values may be of particular use in evaluating multiple alternative SAHES sizing and specification options. This is reflected in the use of this metric in related software applications such as Merit and Homer (Born, 2001; NREL, n.d.).

The number of responsive hours which occurred in each scenario was used to further verify this analysis. These values ranged from 0 to 24, thus highlighting the variation that can occur across the modelled scenarios.

Both of the instances where no responsive hours were recorded occur under the VCPP strategy (during mean RES conditions on the spring seasonal day, and during maximum RES conditions on the winter seasonal day). These instances result from the lack of price variation which occurs under VCPP in these scenarios, which in turn means that there is no financial driver of DR.

Table 7-7 shows the number of responsive hours achieved in each of the scenarios in tabular form.

Table 7-7 - The number of responsive hours achieved in each of the modelled scenarios.

		Variable Pricing Strategy		
Scenario		VToU	RTP	VCPP
Winter	Min RES	16	24	20
	Mean RES	12	22	13
	Max RES	20	23	0
Spring	Min RES	19	21	20
	Mean RES	10	21	0
	Max RES	19	21	16
Summer	Min RES	20	15	17
	Mean RES	12	12	10
	Max RES	19	21	15
Autumn	Min RES	20	20	20
	Mean RES	18	22	20
	Max RES	22	20	18
	Average	*17.2*	*20.3*	*14.1*
	Min	*10*	*12*	*0*
	Max	*22*	*24*	*20*

The RTP strategy achieves the highest average number of responsive hours across all scenarios with 20.2. The VToU strategy is next with an average of 17.3 hours and VCPP (largely as a result of the two zero values) has the lowest average of 14.1 hours. This ranking is also reflected in the fact that RTP achieves the highest number of responsive hours in 8 of the 12 scenarios, with VToU achieving most in 2 scenarios and VCPP in none (though it should be noted that an equal number of responsive hours are achieved on 1 occasion, and that VCPP out-performs either RTP or VToU on 5 occasions).

We can also gain a better understanding of the effectiveness of the DR in each result by calculating the improvement in $r_{d:RES}$ which results from each responsive hour, on average, for each result. This can also be viewed as an indication of the effectiveness of the DR actions taken by the community, by quantifying their impact upon the demand-supply match. This again shows VToU to be the most effective of the three strategies, with an average improvement in $r_{d:RES}$ of 1.97×10^{-3} for every responsive hour. VCPP yields an average of 0.91×10^{-3} while RTP yields 0.89×10^{-3}. Both VToU and RTP have two occurrences of a decrease in $r_{d:RES}$ for every responsive hour, again highlighting the potential for DR to be counter-productive - a significant finding. In the case of RTP during mean RES conditions in the summer seasonal day, 12 responsive hours ultimately result in a decrease in $r_{d:RES}$ - the greatest negative impact on $r_{d:RES}$ of all results. Such counter-productive results notably do not occur under VCPP, which never results in a decrease in $r_{d:RES}$. For example, in instances where VCPP results in no change in $r_{d:RES}$, no responsive hours are recorded, meaning that this strategy only results in DR when a positive impact is to be made on $r_{d:RES}$.

7.2.2 Extent of community-wide DR

The extent to which the community as a whole engages in DR in response to variable energy pricing is quantified by the community-wide r_d value, with lower values representing greater levels of DR. This indicator refers to the impact on the match between the original community demand profile and the one which results from exposure to variable pricing. Figure 7-13 to Figure 7-15 show the community r_d values for all of the modelled scenarios.

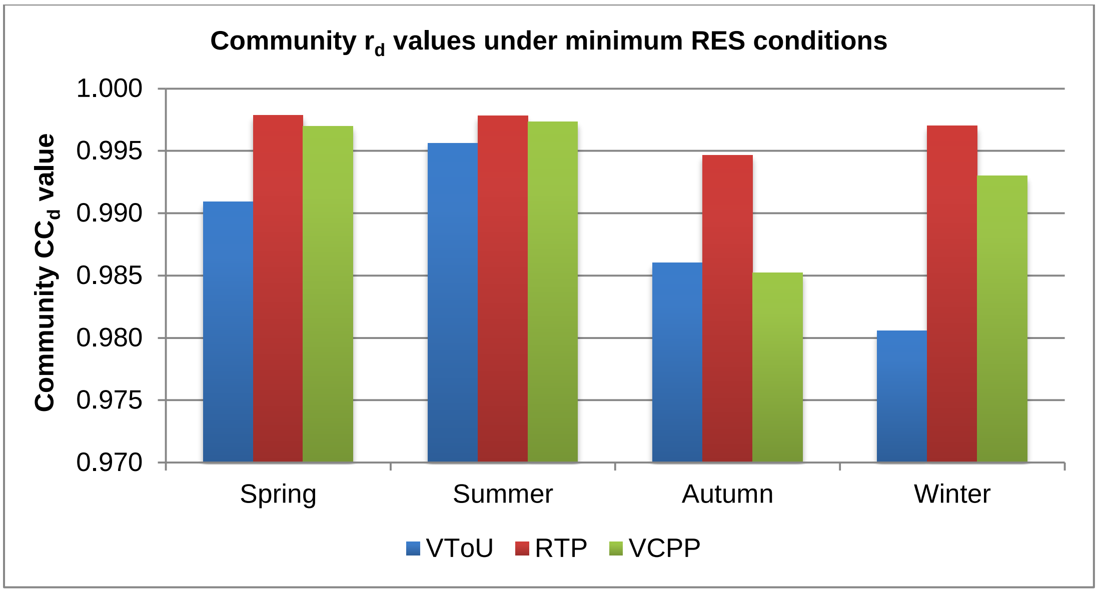


Figure 7-13 - Graph showing community demand profile correlation coefficients during minimum RES conditions.

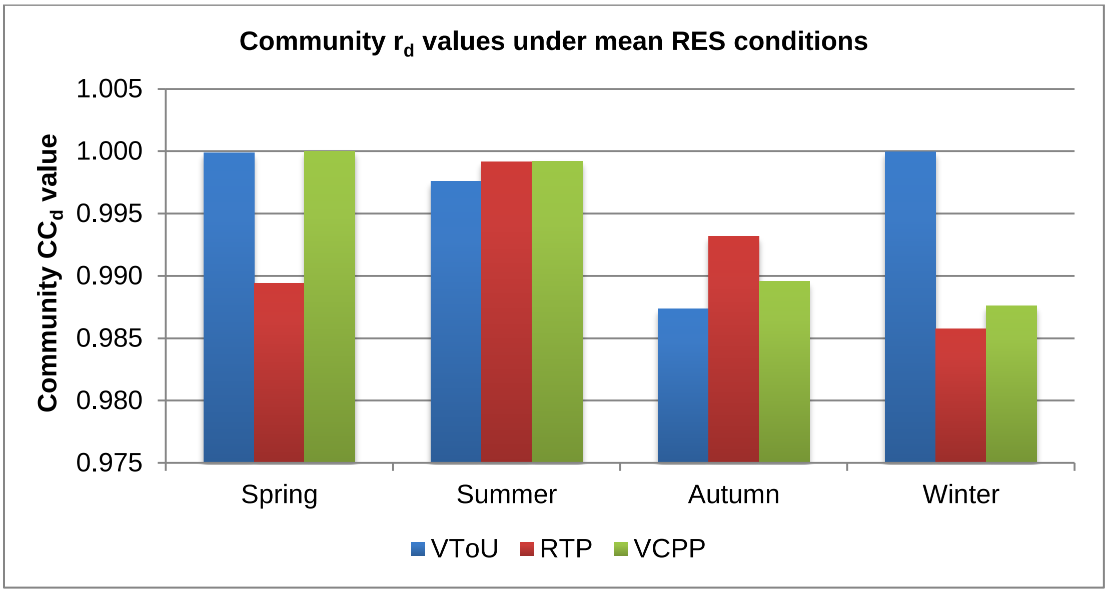


Figure 7-14 - Graph showing community demand profile correlation coefficients during mean RES conditions.

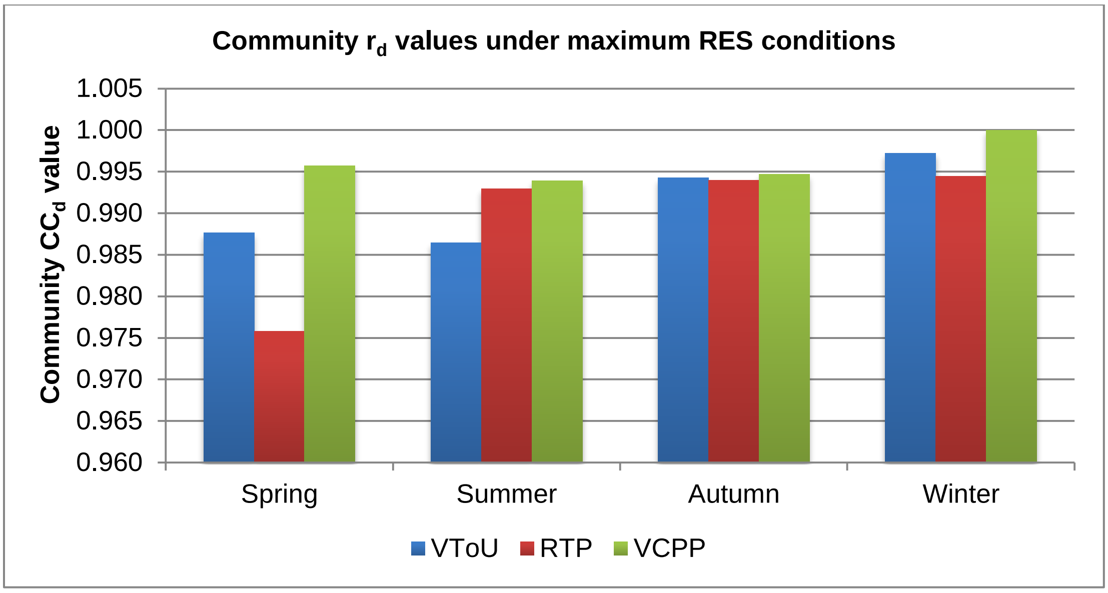


Figure 7-15 - Graph showing community demand profile correlation coefficients during maximum RES conditions.

These graphs also illustrate the ability of variable energy pricing strategies to promote DR at a community-wide level. Results range from a minimum of 0.976 (under RTP during maximum RES conditions in the spring seasonal day) to a maximum of 1.000, which indicates no change in r_d (a result which occurred in 4 of the 36 modelled scenarios). Across all the results the difference in the average r_d achieved by each of the pricing strategies is minimal (VToU has the lowest average value of 0.992, while VCPP has the highest with 0.994). The RTP strategy is the only one not to return an r_d value of 1.000 in any of the modelled scenarios, with the other strategies each returning it on 2 occasions. RTP also results in the greatest range of r_d values, with results varying between a minimum of 0.976 and a maximum of 0.999. However it is the VToU strategy which returns the lowest values on most occasions (6 of the 12 scenarios). The results for all 36 scenarios are shown in Table 7-8.

Table 7-8 - The r_d values achieved in each of the modelled scenarios.

Scenario		Variable Pricing Strategy VToU	RTP	VCPP
Winter	Min RES	0.981	0.997	0.993
	Mean RES	1.000	0.986	0.988
	Max RES	0.997	0.994	1.000
Spring	Min RES	0.991	0.998	0.997
	Mean RES	1.000	0.989	1.000
	Max RES	0.988	0.976	0.996
Summer	Min RES	0.996	0.998	0.997
	Mean RES	0.998	0.999	0.999
	Max RES	0.986	0.993	0.994
Autumn	Min RES	0.986	0.995	0.985
	Mean RES	0.987	0.993	0.990
	Max RES	0.994	0.994	0.995
	Average	*0.992*	*0.993*	*0.994*
	Min	*0.981*	*0.976*	*0.985*
	Max	*1.000*	*0.999*	*1.000*

Broadly speaking, the r_d results largely mirror those of $r_{d:RES}$, with smaller r_d values corresponding with the larger increases in $r_{d:RES}$. However, this is not always the case. For example, the lowest r_d value was returned under RTP during maximum RES conditions in the spring seasonal day, but the greatest increase in $r_{d:RES}$ occurred under VToU during minimum RES conditions in the autumn seasonal day. This means that changes in community demand profile do not necessarily translate into increases in the match between demand and RES, and that as a result $r_{d:RES}$ values cannot be used to predict r_d values, and vice-versa. This disparity can be attributed to the fact that the relationship between demand and RES profiles varies in each scenario. This means that a small change in the pattern of consumption in one set of circumstances can have a more profound impact on the demand-supply match than the same change in demand would during a different set of circumstances. These differences justify the inclusion of both r_d and $r_{d:RES}$ metrics in the results analysis.

By considering both the community r_d values and $r_{d:RES}$ values together, we can gauge the effectiveness of the DR enacted in each scenario by examining whether or not a change in demand (r_d) resulted in the primary desired outcome - an increase in the demand-supply match ($r_{d:RES}$).

This is exemplified by the comparison of the results of the VToU and VCPP pricing strategies under minimum RES conditions in the autumn seasonal day. Despite both strategies having near identical r_d values (0.986 for VToU and 0.985 for VCPP), the corresponding increases in $r_{d:RES}$ vary dramatically, with VToU (0.084) achieving an increase over six times that achieved by VCPP (0.013). This suggests that under these RES conditions, VToU is far more effective than VCPP at achieving an improvement in the match between demand and RES, since it achieves a far greater improvement in the demand-supply match than VCPP, but for a similar level of DR engagement. However, this variation in effectiveness is not consistent across all scenarios. For instance, during mean RES conditions in the summer seasonal day, both VToU and VCPP achieve an increase in $r_{d:RES}$ of 0.01, with VCPP this time requiring less change in r_d to achieve it (though the disparity in this instance is far smaller than in the previous example).

The relationship between these two indicators can be examined in more detail by dividing the change in $r_{d:RES}$ by the r_d for each of the 36 modelled scenarios. This shows the improvement in the demand-supply match which results from the change in demand profile for each scenario, and can therefore be seen as a measure of the effectiveness of the DR which occurs in each scenario. The resulting values are shown in Table 7-9.

Table 7-9 - The impact of changes to the demand profile upon the demand-supply match for each of the modelled scenarios.

		Variable Pricing Strategy		
Scenario		VToU	RTP	VCPP
Winter	Min RES	0.046	0.030	0.019
	Mean RES	-0.001	0.000	0.008
	Max RES	0.012	0.026	0.000
Spring	Min RES	0.033	-0.017	0.024
	Mean RES	-0.001	0.045	0.000
	Max RES	0.079	0.073	0.022
Summer	Min RES	0.051	0.015	0.028
	Mean RES	0.010	-0.025	0.010
	Max RES	0.062	0.035	0.018
Autumn	Min RES	0.085	0.027	0.014
	Mean RES	0.044	0.015	0.029
	Max RES	0.029	0.020	0.015
	Average	*0.038*	*0.020*	*0.016*

VToU can be seen to result in the most effective DR, with the highest average change in $r_{d:RES}$ per change in r_d.

7.2.3 Community DR engagement rate

The community DR engagement rate refers to the proportion of households which engage in DR in a given scenario. The calculation of this rate again involves the use of household r_d values for every household in the model, with those with a r_d value of less than 1 being deemed to have engaged in DR. Figure 7-16 to Figure 7-18 show the community DR engagement rates for each of the modelled scenarios.

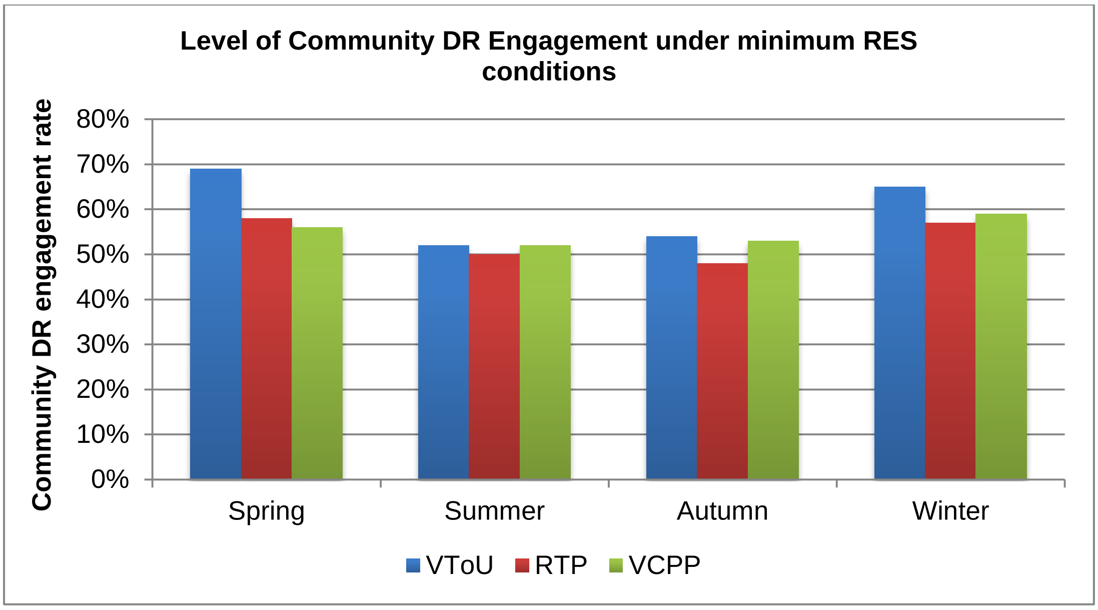


Figure 7-16 - Graph showing the levels of community DR engagement achieved under minimum RES conditions.

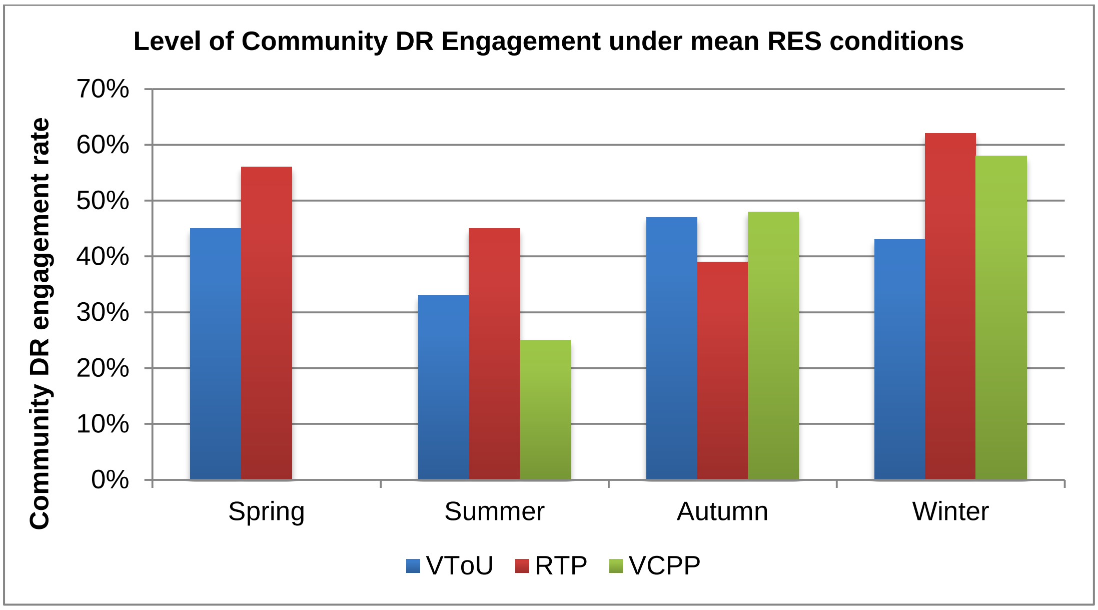


Figure 7-17 - Graph showing the levels of community DR engagement achieved under mean RES conditions.

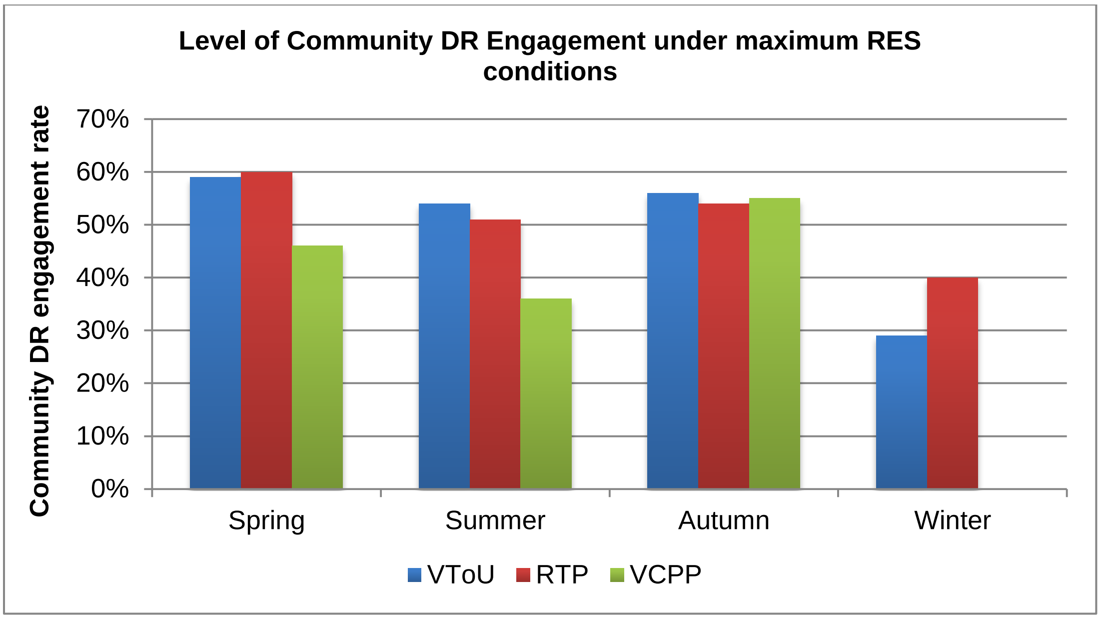


Figure 7-18 - Graph showing the levels of community DR engagement achieved under maximum RES conditions.

Table 7-10 shows the DR engagement rates for all 36 scenarios.

Table 7-10 - The community-wide DR engagement rates achieved in each of the modelled scenarios.

Scenario		Variable Pricing Strategy		
		VToU	RTP	VCPP
Winter	Min RES	65%	57%	59%
	Mean RES	43%	62%	58%
	Max RES	29%	40%	0%
Spring	Min RES	69%	58%	56%
	Mean RES	45%	56%	0%
	Max RES	59%	60%	46%
Summer	Min RES	52%	50%	52%
	Mean RES	33%	45%	25%
	Max RES	54%	51%	36%
Autumn	Min RES	54%	48%	53%
	Mean RES	47%	39%	48%
	Max RES	56%	54%	55%
	Average	*51%*	*52%*	*41%*
	Min	*29%*	*39%*	*0%*
	Max	*69%*	*62%*	*59%*

Results range from 0% (a result which occurs on the aforementioned 2 occasions under VCPP) to 69% (under VToU during minimum RES conditions in the spring seasonal day) with RTP returning the highest mean rate across all results (52%) when compared with VToU (51%) and VCPP (41%). Table 7-10 also shows RTP to be the most consistent of the three strategies, with the range of engagement rates varying by just 23%, in comparison to 40% for VToU and 59% for VCPP.

By dividing the r_d value for each scenario by the community wide DR engagement rate, it is possible to quantify the mean contribution made by each responsive household. The results of this analysis are presented in Table 7-11, which shows the results for all instances where DR occurs i.e. the two scenarios during which VCPP fails to result in DR are excluded. This shows VCPP to be the strategy under which the average responsive household contributes the least towards community level DR i.e. the DR is shared across the greatest number of households.

Table 7-11 - Quantification of the contribution to community-level DR made by the average responsive household in each modelled scenario.

Scenario		Variable Pricing Strategy: VToU	RTP	VCPP
Winter	Min RES	0.985	0.983	0.983
	Mean RES	0.977	0.984	0.983
	Max RES	0.966	0.975	-
Spring	Min RES	0.986	0.983	0.982
	Mean RES	0.978	0.982	-
	Max RES	0.983	0.984	0.978
Summer	Min RES	0.981	0.980	0.981
	Mean RES	0.970	0.978	0.960
	Max RES	0.982	0.981	0.972
Autumn	Min RES	0.982	0.979	0.981
	Mean RES	0.979	0.975	0.979
	Max RES	0.982	0.982	0.982
	Average	*0.979*	*0.980*	*0.978*
	Min	*0.966*	*0.975*	*0.960*
	Max	*0.986*	*0.984*	*0.983*

7.2.4 Change in peak demand

As discussed previously, the impact of DR upon peak demand remains a highly relevant and desirable outcome of DR in this context, despite not being the primary aim.

Figure 7-19 to Figure 7-21 show the impact of variable pricing upon community-wide peak demand under all the modelled scenarios.

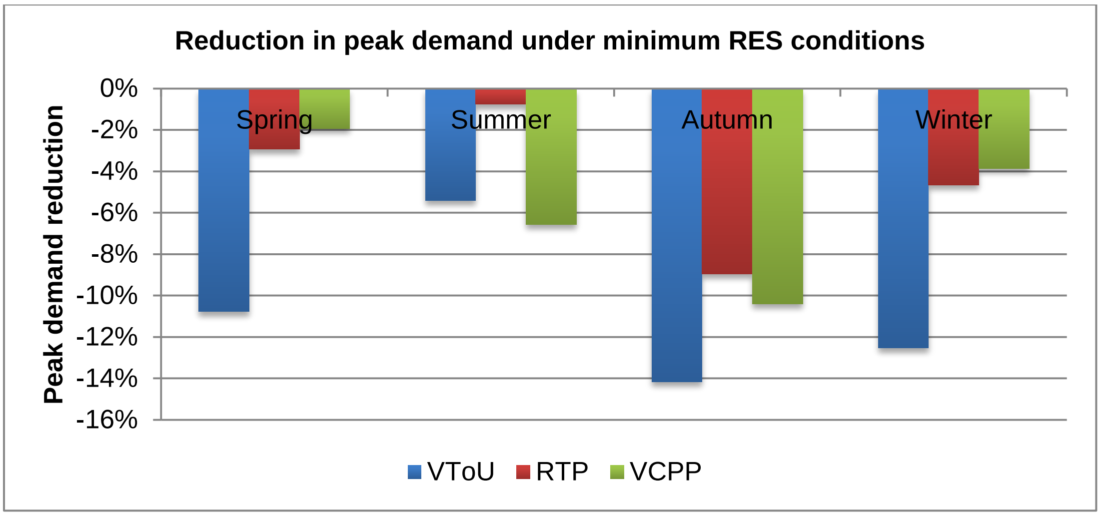


Figure 7-19 - Graph showing the peak demand reduction achieved during minimum RES conditions.

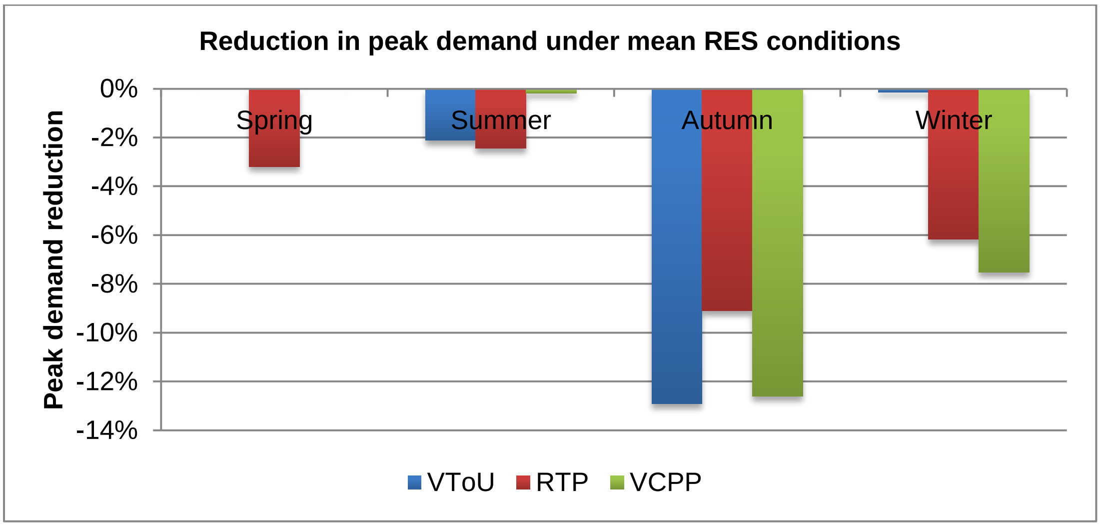


Figure 7-20 - Graph showing the peak demand reduction achieved during mean RES conditions.

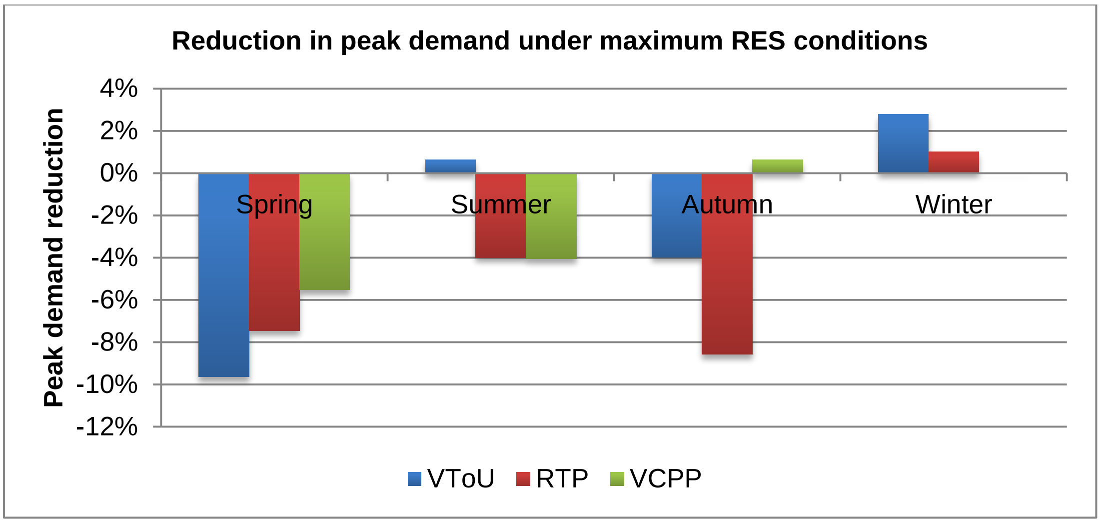


Figure 7-21 - Graph showing the peak demand reduction achieved during maximum RES conditions.

The results for all 36 scenarios are shown below in Table 7-12.

Table 7-12 - The community-wide peak demand reduction achieved in each of the modelled scenarios.

		Variable Pricing Strategy		
Scenario		VToU	RTP	VCPP
Winter	Min RES	-12.5%	-4.7%	-3.9%
	Mean RES	-0.1%	-6.2%	-7.5%
	Max RES	2.8%	1.0%	0.0%
Spring	Min RES	-10.8%	-2.9%	-1.9%
	Mean RES	0.0%	-3.2%	0.0%
	Max RES	-9.6%	-7.4%	-5.5%
Summer	Min RES	-5.4%	-0.8%	-6.6%
	Mean RES	-2.1%	-2.4%	-0.2%
	Max RES	0.6%	-4.0%	-4.1%
Autumn	Min RES	-14.2%	-8.9%	-10.4%
	Mean RES	-12.9%	-9.1%	-12.6%
	Max RES	-4.0%	-8.6%	0.6%
	Average	*-5.7%*	*-4.8%*	*-4.3%*
	Min	*-14.2%*	*-9.1%*	*-12.6%*
	Max	*2.8%*	*1.0%*	*0.6%*

The varying extent of RES deficit in each scenario means that the driver for peak demand reduction - high energy prices - also varies. This in turn causes the variation in the levels of demand reduction achieved in each of the scenarios to vary significantly. The timing of the high pricing periods also affects the ability of consumers to reduce their demand, with shiftable and curtailable loads being more likely to be used at certain times of day. Also, the fact that peak demand reduction is not the primary goal of the variable pricing strategies also means that peak reduction is considered a secondary benefit.

Nevertheless, the results provide a useful insight. VToU is found to return the greatest average peak demand reduction across all of the modelled scenarios, followed by RTP. This is aided significantly by the comparatively high levels of DR achieved under minimum RES conditions, where VToU averages a 10.7% peak reduction, in comparison to 5.7% for VCPP and 4.3% for RTP. VToU also results in the greatest range of peak demand reduction values, with results varying by up to 17% when compared to a variation of 13.2% for VCPP and just 10.1% for RTP. The greatest reduction in peak demand, 14.2%, is achieved by VToU under minimum RES conditions on the autumn seasonal day - the result which also returns the greatest increase in the demand-supply match (as indicated by $r_{d:RES}$). This result initially appears to be at odds with the fact that - as discussed previously - the RTP strategy is capable of more accurately reflecting the demand-RES supply balance. However, since the VToU strategy uses a smaller number of greater changes in price, it is capable of achieving a greater response. This is due to the fact that when the RES supply/deficit level moves from one RTP pricing bracket to another, then change in price (and therefore the change in the resulting DR) is less pronounced than if the same happens under VToU, where a larger change in price causes a greater response. The fact that VToU outperforms RTP in this regard suggests that this effect outweighs the benefits of the increased number of smaller responses which occur under RTP and not under VToU.

That VCPP should not be the strategy which achieves the greatest level of peak demand reduction is surprising given the inclusion of the 'super-peak' pricing level - a high pricing point designed to disincentivise consumption during periods when RES deficit is at its greatest. However, the fact that the range of prices which occur under each strategy is limited in order to maintain consistent peak-to-minimum pricing ratios is likely to limit the effectiveness of this measure.

Under maximum RES conditions, peak demand is found to increase on four occasions, as visible above in Figure 7-21. The VToU strategy twice results in an increase in peak demand, with RTP and VCPP both achieving this once. The demand and RES profiles associated with the greatest of the peak demand increases is shown in Figure 7-22.

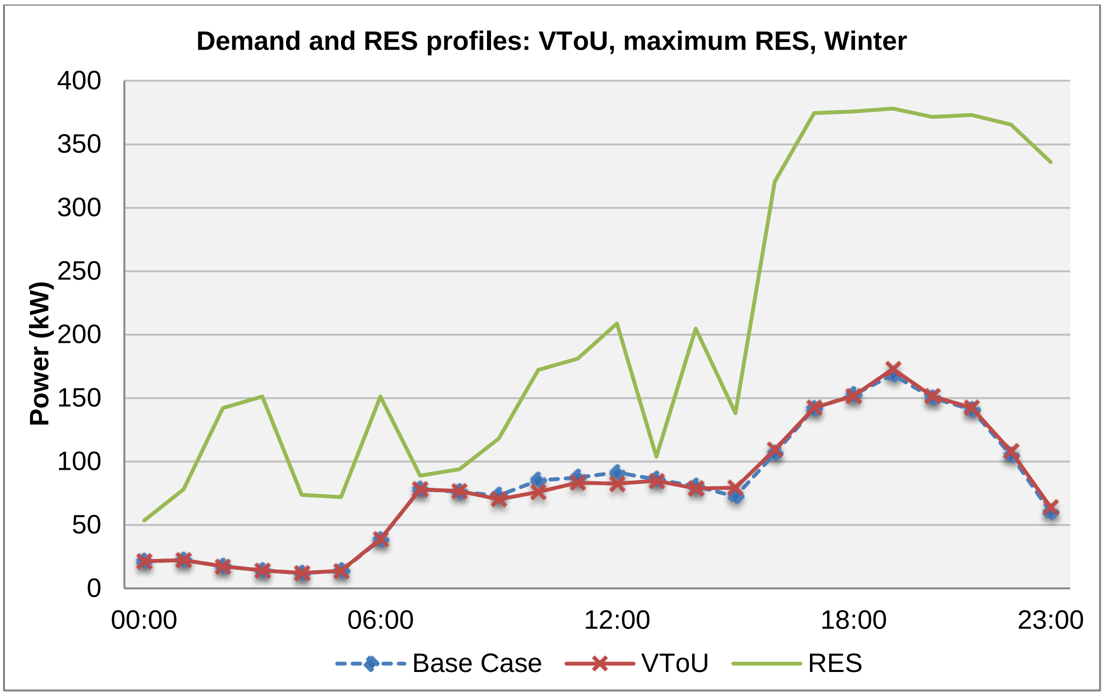


Figure 7-22 - Graph showing demand and RES profiles associated with maximum peak demand increase.

This graph shows that the seasonal day in question, winter, has no periods of predicted RES deficit i.e. RES always exceeds demand. The variable pricing strategies (in this case VToU) therefore promotes load growth to consumers by reducing the cost of energy. Since price is governed primarily by RES surplus/deficit, this cost reduction is at its greatest during times of peak RES surplus (between the hours of 17:00 and 23:00).

7.3 Household Level Results

When considering results from a household perspective the focus of the analysis also changes, from system-level indicators which would likely be at the forefront of the SAHES designer and operator’s considerations to the impact of DR upon individual households. Household level results analysis also serves to highlight any outcomes or trends which may have significant impact upon the socio-economic viability of variable energy pricing.

7.3.1 Extent of household level DR

The extent to which each household engages in DR is assessed using similar indicators to those used in the community level analysis. At this level, r_d values refer to the demand profiles of individual households rather than the whole community.

Since some households have characteristics which enable them to engage in greater levels of DR than others (such as elasticity levels, appliance usage, the use of electric water heating etc.) household level r_d values vary considerably more than the community wide values. A minimum household r_d of 0.114 occurs under the VCPP strategy during maximum RES conditions on the summer seasonal day. VToU has a minimum of 0.192 and RTP 0.259, occurring under the same conditions. Figure 7-23 to Figure 7-25 show the household demand profiles associated with these figures, and provide a clearer representation of the resulting impact on household energy consumption patterns.

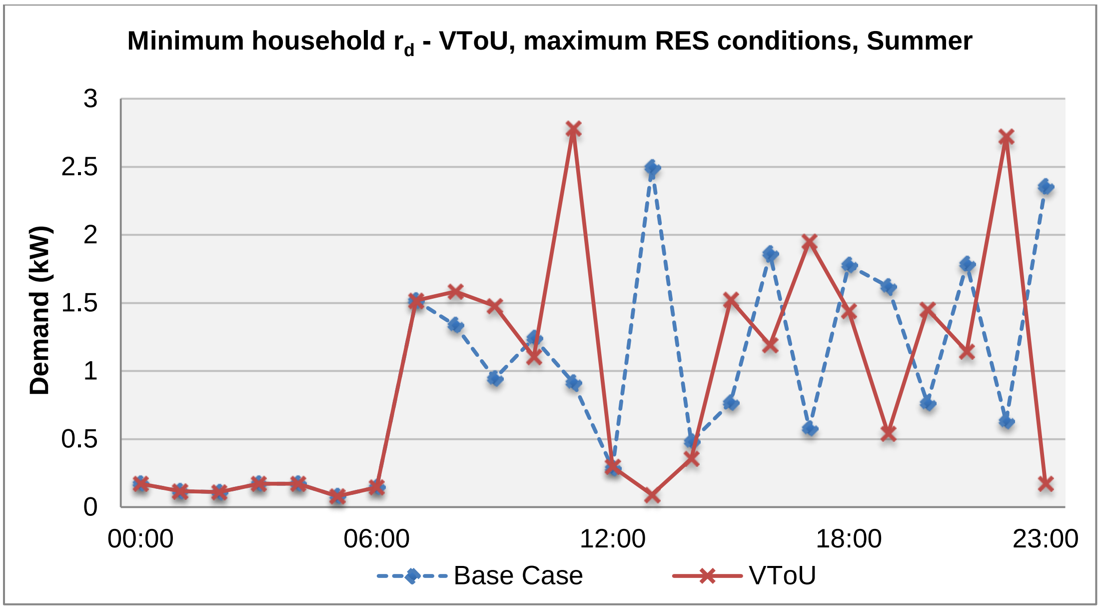


Figure 7-23 - Graph showing minimum r_d achieved under VToU.

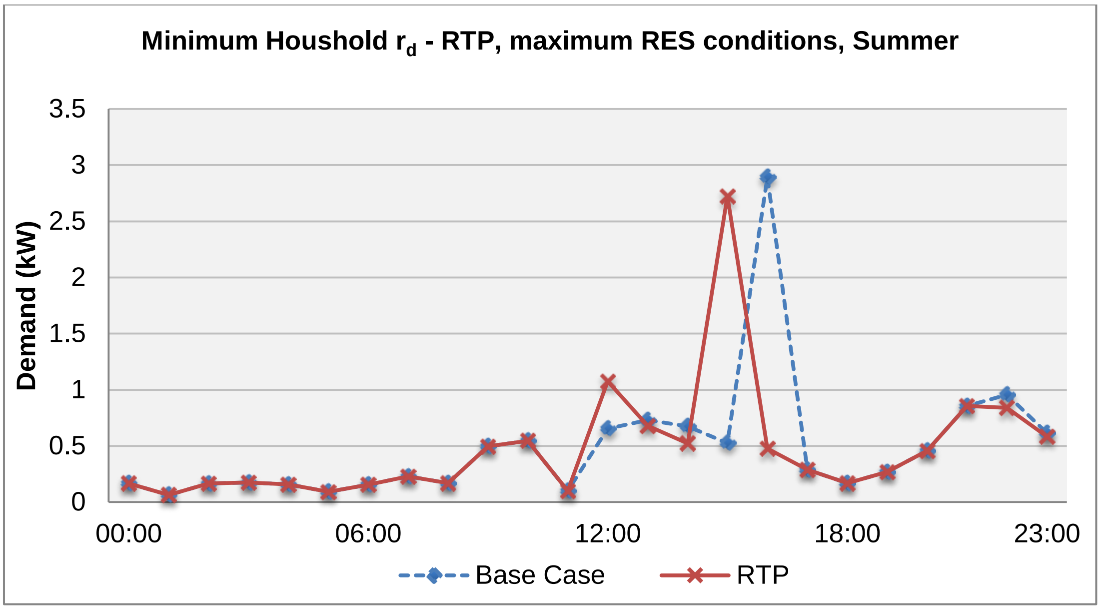


Figure 7-24 - Graph showing minimum r_d achieved under RTP.

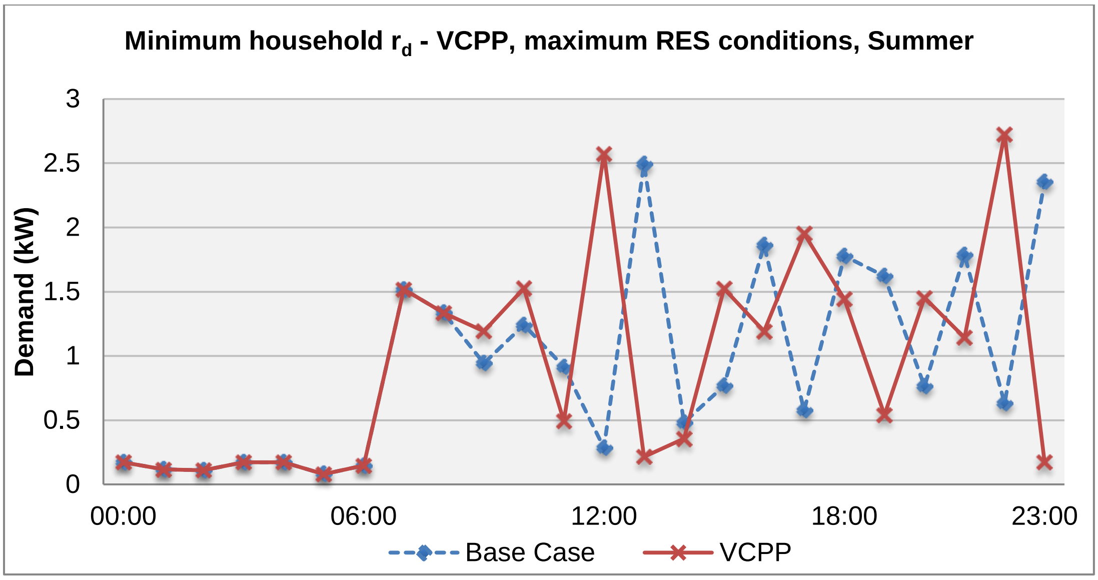


Figure 7-25 - Graph showing minimum r_d achieved under VCPP.

It should be noted that profiles shown in Figure 7-23 and Figure 7-25 are taken from the same household (the variation that occurs between households will be discussed further below). These graphs illustrate the level of potential disruption to predicted energy consumption patterns that can be caused by exposure to variable energy pricing. However, it should again be noted that some changes in demand are more disruptive than others, with some being effectively imperceptible to householders e.g. the shifting of electric water heating loads. The dominant form of DR in each of the three strategies' minimum r_d instances is load shifting, with only the RTP instance (Figure 7-24) resulting in a change in the overall daily consumption, in the form of a 1.3% reduction on the base case daily total. In all three instances the variable pricing has caused shiftable loads to be brought forward by 1-2 hours in order to better suit RES conditions (in accordance with the main aims of the variable pricing strategies). Both Figure 7-23 and Figure 7-25 feature no change in the level of overall household consumption as a result of DR, but both see an increase in peak demand as a result of the load shifting which takes place.

7.3.2 Impact on household energy bills

Household energy bills are a function of energy consumption and energy price. Given that the price of energy varies according to levels of RES surplus/deficit under the pricing strategies developed in this study, it follows that bills can be expected to be higher during periods of RES deficit and lower during periods of RES surplus. The results reflect this, with minimum RES conditions resulting in increased mean household bills and an increased range of bill amounts, as shown in Figure 7-26. This graph plots the minimum, mean (denoted by the marker) and maximum daily household bills that occur under each pricing strategy, as well as the second and third quartile limits, which form the bottom and top edges of the boxes respectively. The first and fourth quartiles are represented by the lines extending from the boxes, with maximum and minimum values forming the limits of the lines.

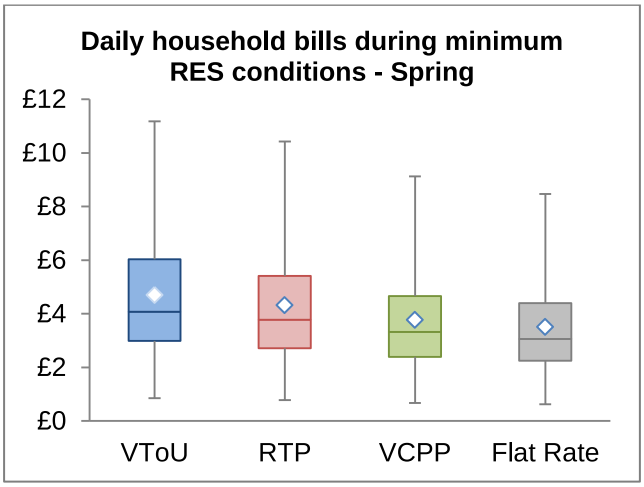


Figure 7-26 - Box plot showing household bill variation during minimum RES conditions in the spring seasonal day.

Figure 7-26 shows the increase in bill variation that occurs under all three variable pricing strategies, which comes primarily as result of increases in maximum bills rather than decreases in minimum bills. This is clearly illustrated in the associated frequency distribution curves for this scenario, shown in Figure 7-27.

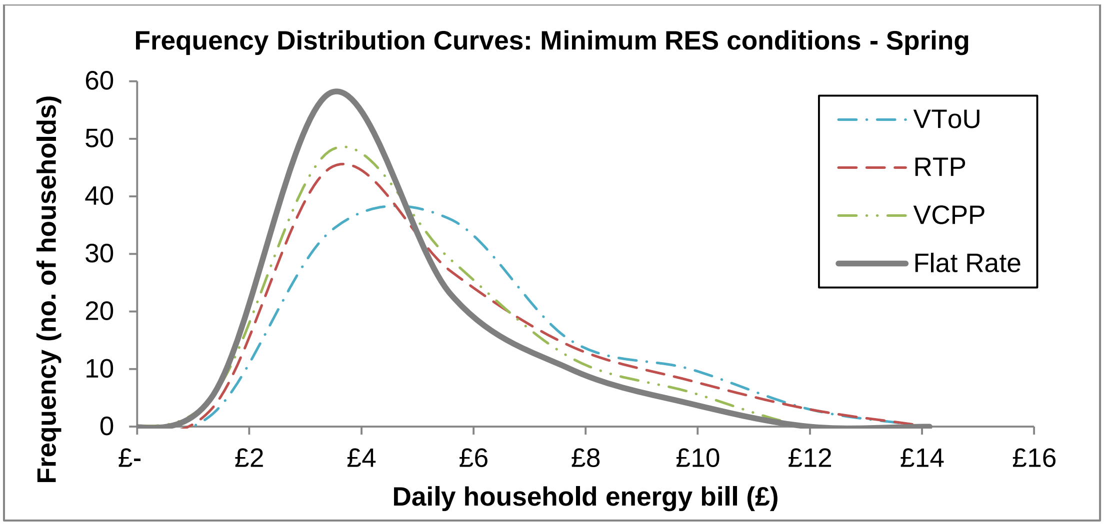


Figure 7-27 - Household energy bill frequency distribution curves during minimum RES conditions - spring seasonal day.

Under this scenario, all three variable pricing strategies result in higher energy bills than the flat rate pricing used as a base case, with VCPP being the closest to matching flat rate pricing and VToU being easily identifiable as resulting in the highest bills.

As expected, under maximum RES conditions the opposite can be seen to be true, as illustrated by Figure 7-28 and Figure 7-29.

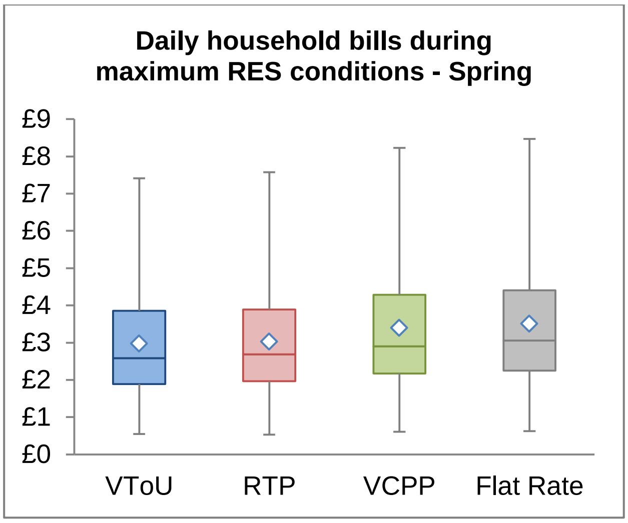


Figure 7-28 - Box plot showing household bill variation during maximum RES conditions in the spring seasonal day.

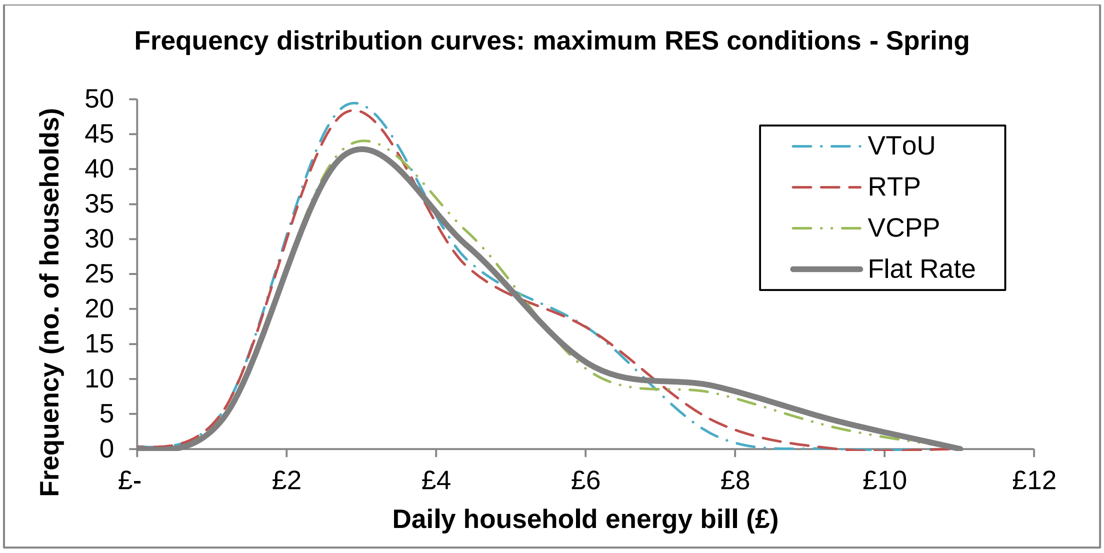


Figure 7-29 - Household energy bill frequency distribution curves during maximum RES conditions - spring seasonal day.

These graphs show that under maximum RES conditions, flat rate pricing clearly results in higher prices than all three variable pricing strategies, with VToU identifiable as having the lowest bills in this instance. Again the main differences stem from decreases in the highest bills and the most frequent bill amounts. This result is repeated during the other 3 seasonal days

Under mean RES conditions, the amount of RES surplus or deficit which occurs can vary more significantly, and as such the results show less variation between pricing strategies.

Across all of the modelled scenarios, the changes in household energy bills under variable pricing when compared to flat rate pricing range between a 10.5% increase (under VToU) and a 6.3% decrease (under RTP). If the mean values are taken across all households, it is VToU which returns the greatest average increase of 4% when compared to flat rate pricing. VCPP returns an average decrease of 0.7%, with RTP returning an increase of 0.56% on average.

Whilst bills in real-world applications are likely to vary more significantly over an entire calendar year, this indicates that the overall impact of variable pricing strategies such as those presented would have a limited effect on household energy bills.

Further discussion of how the impact of variable pricing upon household energy bills varies according to key characteristics is provided in the following section.

7.4 Household Type Comparison

The household level analysis of the simulation results conducted above provides some insight as to the impact of variable energy pricing upon households. However, while this characterises the limits of the resultant impacts and provides some indication of the likely impacts that would be felt by the 'average' household, it also serves to illustrate the variation that occur between households. More in-depth comparative analysis is therefore needed in order to establish the extent of this variation, and to identify the household characteristics which play the most significant roles in determining these impacts. This involves grouping the households together according to their main distinguishing characteristics, namely:

1. The number of permanent household occupants.
2. The level of household demand elasticity.
3. The level of household appliance use.

In each case, the results of each group can be collectively assessed using a combination of the metrics used to conduct both community level and household level analyses. The following metrics are used to examine the collective response of each grouping:

- Mean DR engagement rate (determined using r_d values).
- Mean extent of DR (r_d).
- Mean change in daily household energy bills.
- Mean change in peak demand.

7.4.1 Household size

Along with appliance usage levels, the number of occupants who permanently reside at any given household affects the level of demand it is likely to have. By collating the household results into groups of equal household size, it is possible to establish whether this has any bearing on DR.

Figure 7-30 shows the mean DR engagement rate across all of the modelled scenarios and all variable pricing strategies. It shows a variation in DR engagement rate of 21%, with no clearly identifiable trend.

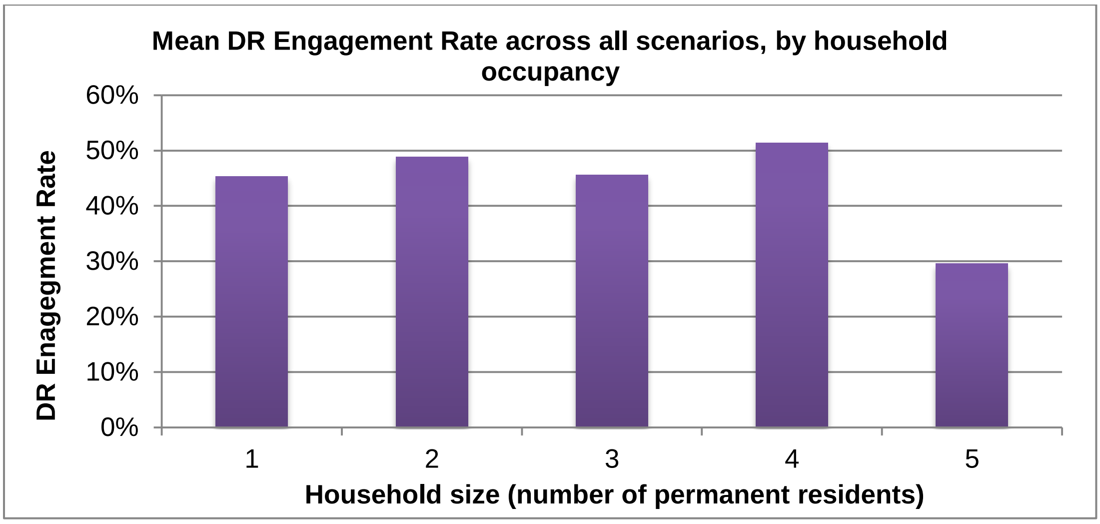


Figure 7-30 - Graph showing mean DR Engagement Rate according to household size.

However, this relationship can be further explored by examining the mean household r_d values, as illustrated in Figure 7-31. This suggests that while most household sizes vary only slightly in the extent to which they modify the shape of their demand profile in response to variable energy pricing, households containing 5 occupants are much less likely to do so, with a mean r_d value of 0.994. It should be noted that this result may be skewed by the comparatively small sample size for households of that size, as the model only contains 3 such households. In households with 1 to 4 occupants, r_d values can be seen to decrease as household size increases, which further suggests that the figures for 5 person households are affected by the small sample size.

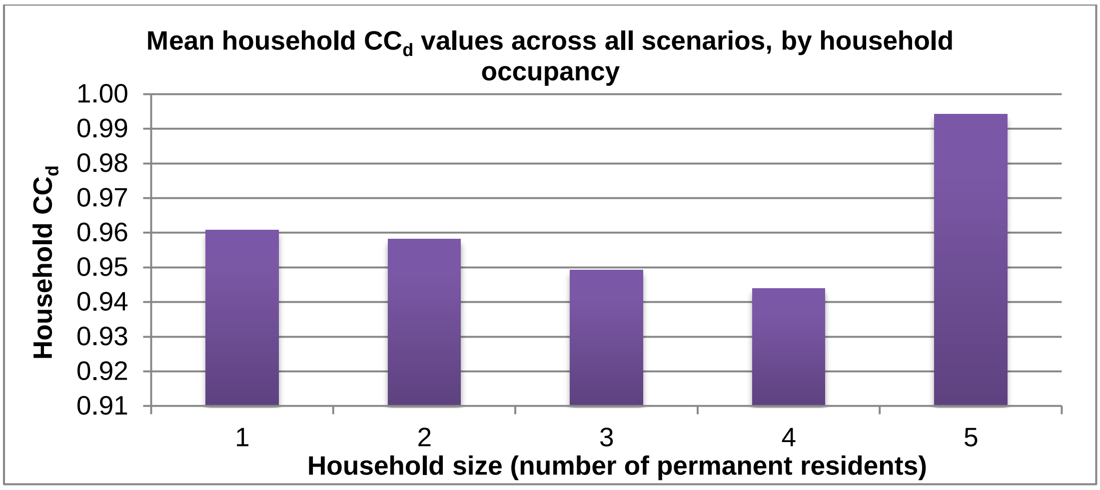


Figure 7-31 - Graph showing mean household r_d values according to household size.

A slightly more identifiable trend is apparent when considering the variation in household energy bills by household size. As shown in Figure 7-32, smaller households are less likely to experience bill increases than larger households, with single person households seeing an average of just 0.9% increase across all of the modelled scenarios, and 5 person households seeing an average of a 3% rise. This can be attributed to the fact that the cost saving resulting from a given DR action is likely to represent a larger proportion of the overall household energy costs for smaller households. Therefore, in order to achieve the same level of cost saving (and subsequent avoidance of bill increases), larger households must engage in more individual DR actions.

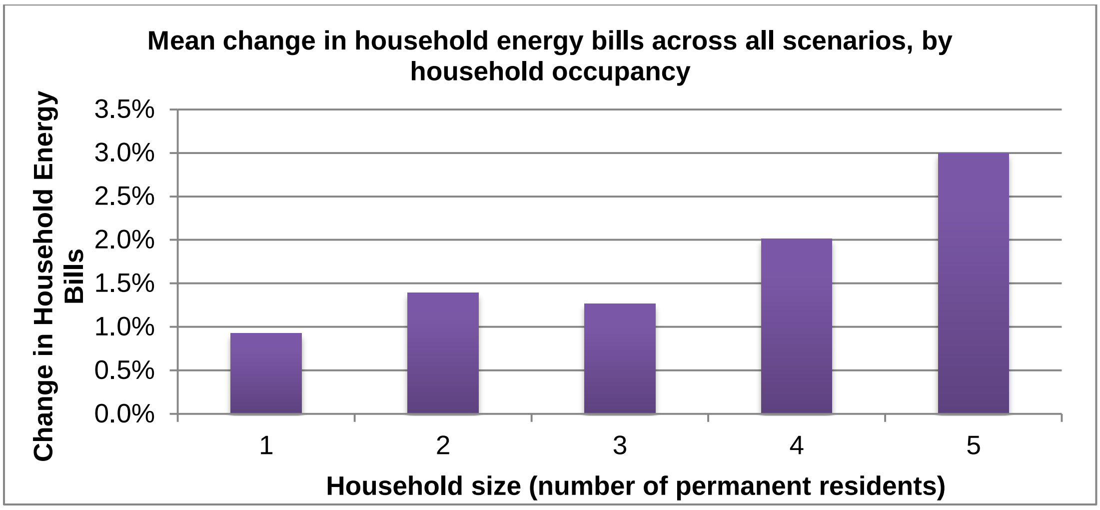


Figure 7-32 - Graph showing mean change in household energy bills according to household size.

Figure 7-33 shows the mean change in household peak demand which occurs across all modelled scenarios. The lack of a clearly identifiable trend suggests that changes in peak demand are not closely linked to household size. Although peak demand reduction can be seen to generally decrease with household size, the relationship between the two variables cannot be seen as strong. Mean figures range from a 2.4% decrease for single person households to a 0.2% increase for 4 person households.

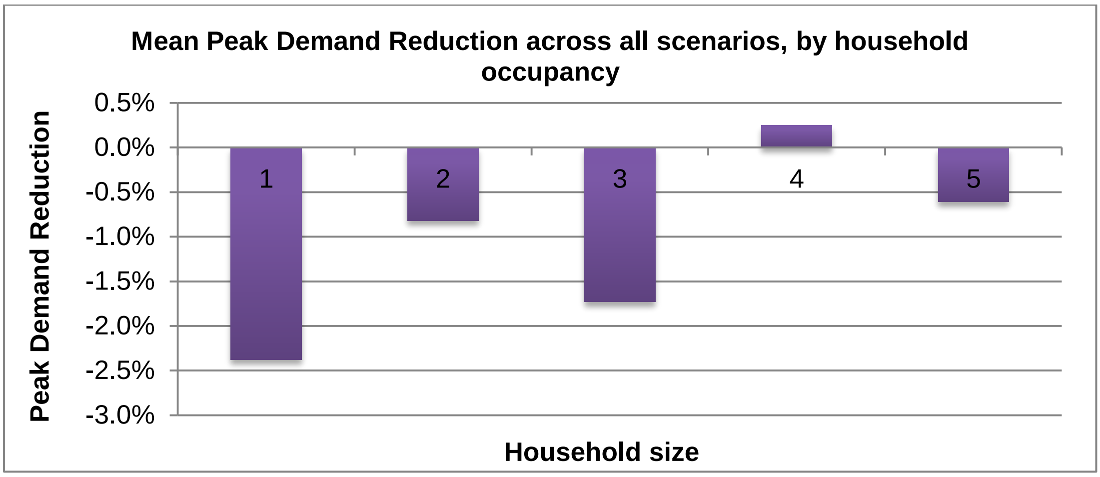


Figure 7-33 - Graph showing mean peak demand reduction according to household size.

7.4.2 Household demand elasticity

Given the role of elasticity values in the calculation of the maximum permissible levels of DR (as featured in the DR algorithm presented in Chapter 5), it is expected that household elasticity levels will be closely linked to scale and extent of DR which results from exposure to variable energy pricing.

Figure 7-34 shows the mean DR engagement rate across all modelled scenarios. It shows that both medium and high elasticity households are similarly likely to engage in DR (with mean DR engagement rates of 61% and 66% respectively), with those with low elasticity far less likely, with a mean engagement rate of just 16%. This result supports the logical inference that DR engagement should increase with household elasticity levels, but appears to suggest that a certain base level of elasticity is required in order to facilitate significant levels of engagement.

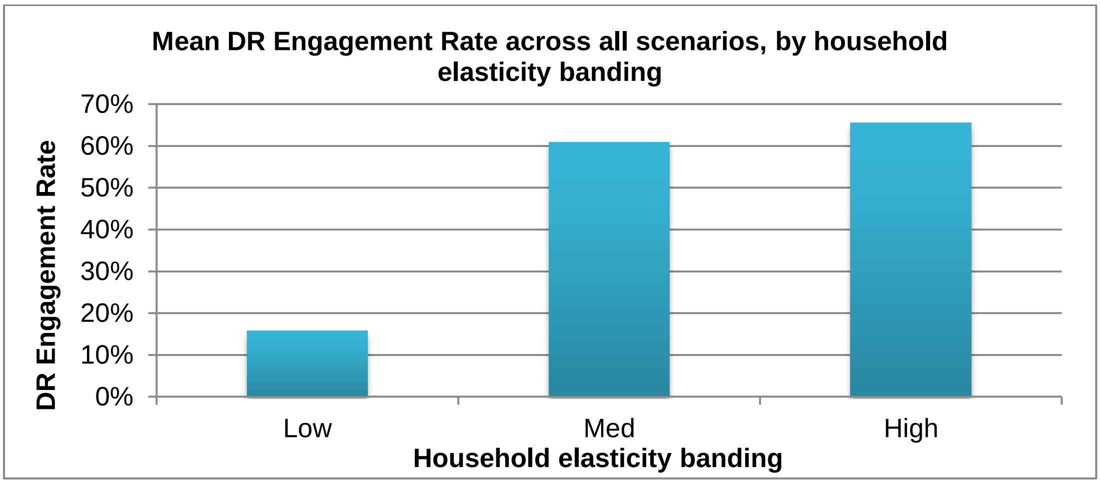


Figure 7-34 - Graph showing mean DR engagement rates according to household elasticity banding.

Household r_d values, shown in Figure 7-35, mirror the DR engagement rate results in that low elasticity households are shown to alter their demand profile shape significantly less than medium and high elasticity households.

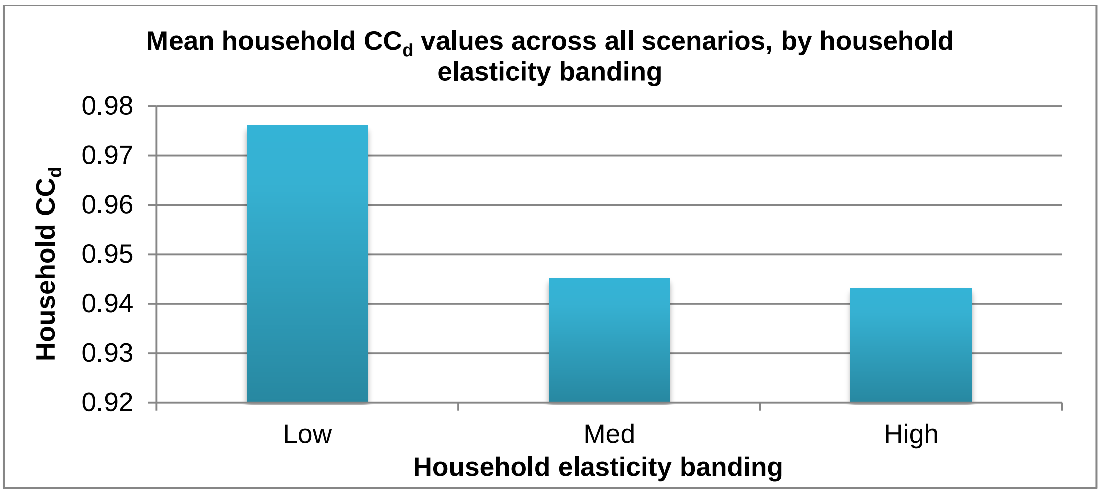


Figure 7-35 - Graph showing mean household r_d values according to household elasticity banding.

Figure 7-36 shows the mean change in daily household energy bills according to household elasticity banding. Whereas the previous metrics have indicated that medium and high elasticity households achieve similar results, in this case it is low and medium elasticity households which see similar results, with high elasticity households seeing far smaller mean bill increases at just 0.1%. Low elasticity households see the greatest increase with 2.2%, while medium elasticity households have slightly less with 1.9%. This shows the DR engaged in by high elasticity households to be far more effective than that engaged in by medium elasticity households when viewed in terms of avoiding bill increases.

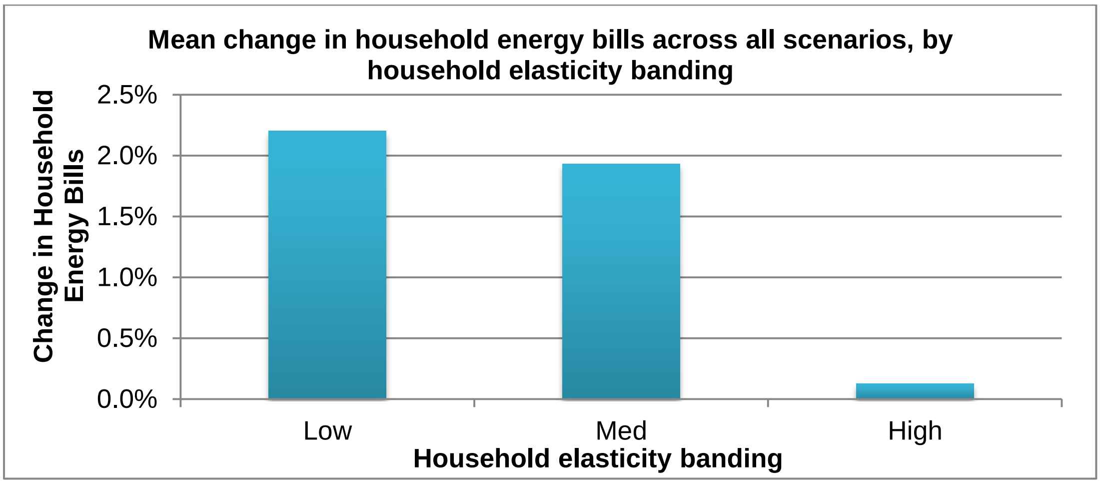


Figure 7-36 - Graph showing mean change in household energy bills according to household elasticity banding.

As is clearly visible in Figure 7-37, peak demand reduction can be seen to increase markedly with household elasticity levels. Low elasticity consumers are found to have a peak demand *increase* of 0.1% on average, with medium and high elasticity households seeing 0.4% and 3.1% decreases respectively.

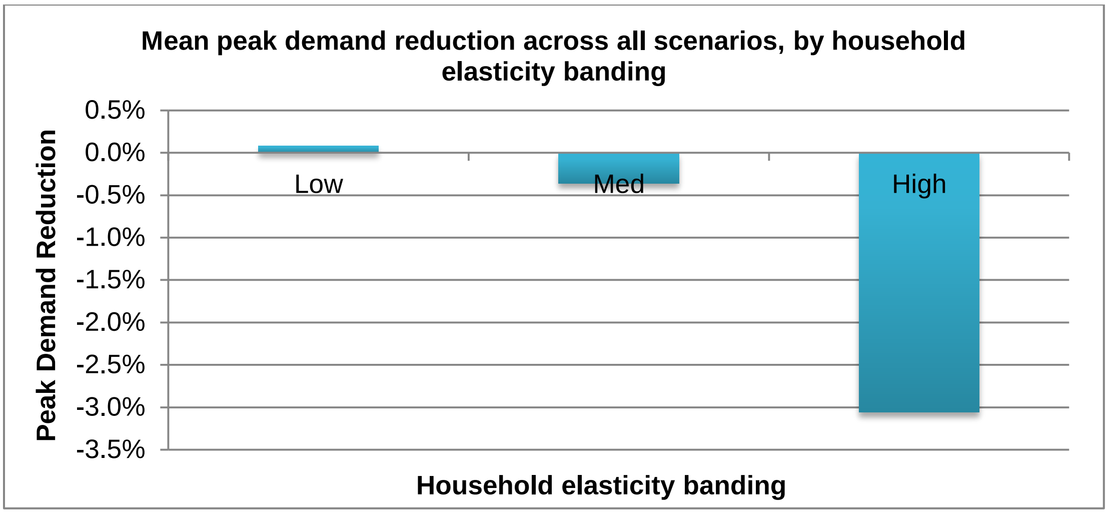


Figure 7-37 - Graph showing mean peak demand reduction according to household elasticity banding.

7.4.3 Household appliance usage

Given the recent upward trend in domestic appliance ownership/usage as discussed in Chapter 3, the impact that this could have on DR is of particular interest not only for this study, but also when considering the long term implications of such a trend and the impact it might have on future DR engagement.

The DR engagement rate of the three appliance use bandings is shown in Figure 7-38, which shows the mean value for each appliance use banding, across all of the modelled scenarios. This result mirrors that of the elasticity bandings, with medium and high bandings (both with a mean engagement rate of 59%) out-performing those in the low banding (with a mean DR engagement rate of 24%) significantly. Given that an increase in appliance use represents an increase in the amount of flexible demand a household has, it follows that this enables greater levels of DR to be engaged in. As per the appliance use bandings described in the previous chapter, households in the low appliance use banding have only two loads which can be curtailed or shifted, as opposed to the medium and high bandings, which have six and ten respectively. The lack of difference between the DR engagement levels in medium to high appliance use groups can be attributed to the fact that the engagement of a household does not convey the *extent* to which DR is engaged in. So while the DR engagement rates are the same, high appliance use households are likely to engage to differing extent than medium appliance use households.

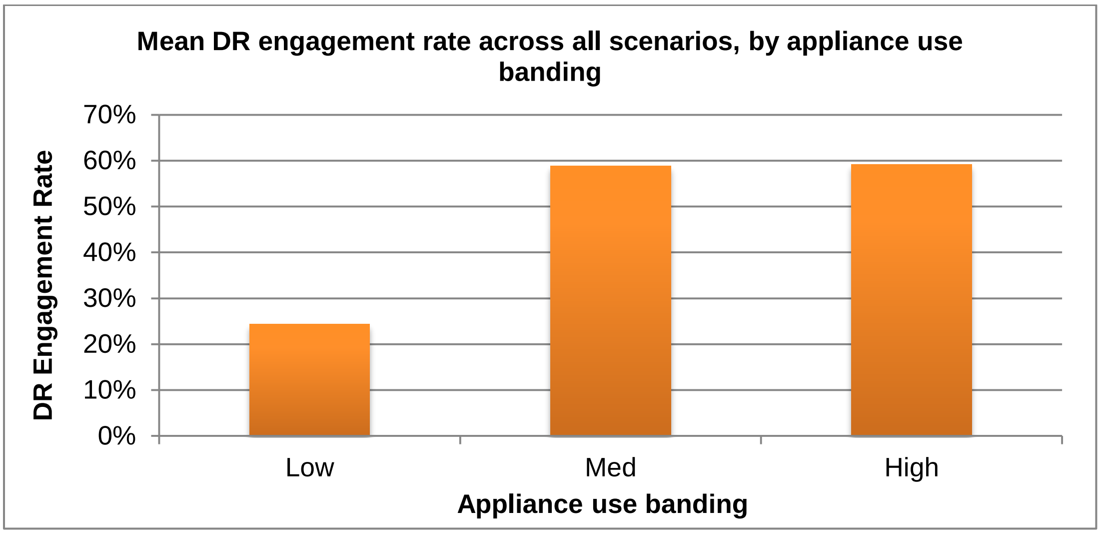


Figure 7-38 - Graph showing mean DR engagement rates according to appliance use banding.

This is corroborated by Figure 7-39, which shows a clear relationship between levels of appliance use and household r_d values. However, rather than the high appliance use households having the lowest r_d values and the low appliance use households having the highest (as was predicted), the results show the opposite to be the case. For the consumer group with the lowest DR engagement rate to have the lowest mean r_d suggests that those consumers in the low appliance use banding who do engage in DR, do so to a greater extent than those in the medium and high appliance use bands. It also stands to reason that if consumption levels are lower in low appliance use household, then any DR will have a greater impact on the overall household consumption pattern (as indicated by r_d) than in households where consumption is higher.

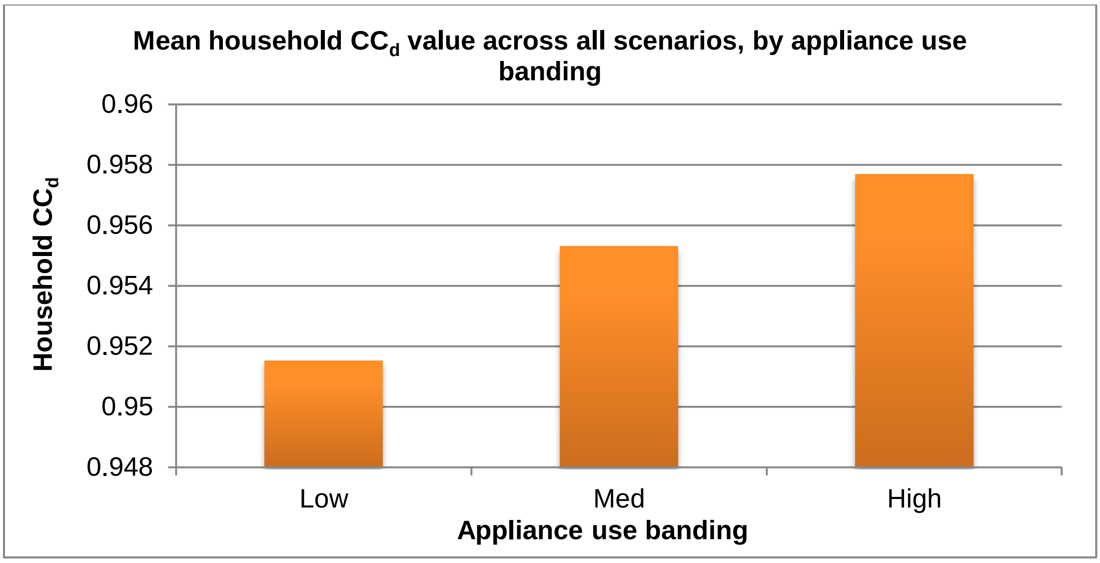


Figure 7-39 - Graph showing mean household r_d values according to appliance use banding.

The mean changes in energy bills experienced by each appliance use banding are shown in Figure 7-40. High appliance use households are found to experience the least increase in their energy bills (0.9%), with the increase experienced by low and medium appliance use households being significantly larger and notably quite similar, at 1.7% and 1.6% respectively.

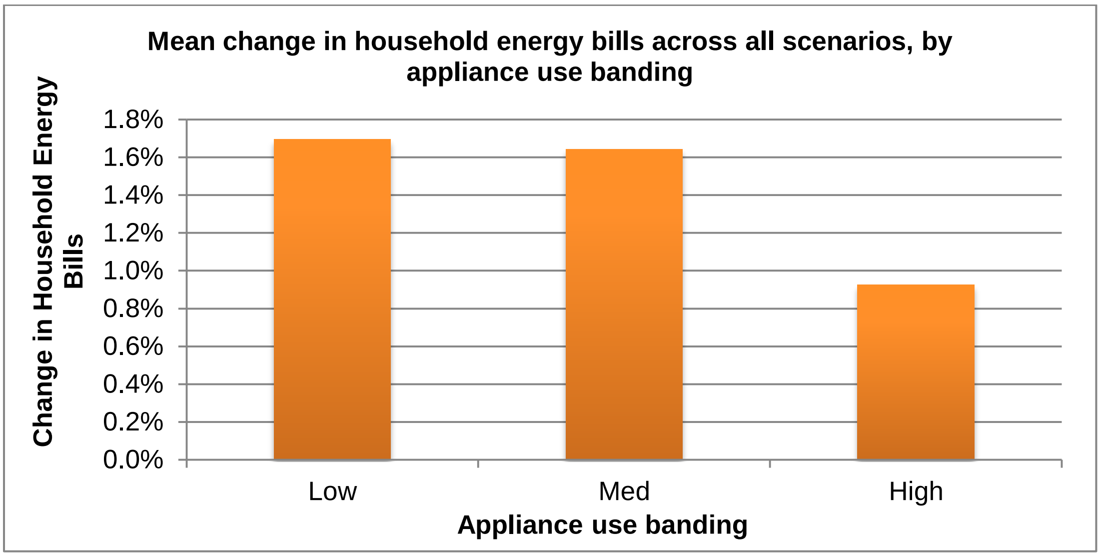


Figure 7-40 - Graph showing mean change in household energy bills according to appliance use banding.

When viewed in combination, the relationship between bill changes (or their avoidance) and DR engagement point to a negative result from the perspective of low appliance use households. The reason for this is that despite engaging to a greater extent (if not in greater numbers) than other groups, the low appliance use group still see the greatest mean increase in their energy bill. This shows that the financial rewards for engaging in DR are not aligned with the extent of the response itself, thereby lessening the incentive for low appliance use households to continue engaging in DR in the first place. Should such a result occur in practice, then this effect would likely be worsened by the fact that high appliance use customers see the lowest bill increase despite varying their consumption pattern the least of all three appliance usage groups.

Lastly, Figure 7-41 shows the mean peak demand reduction according to appliance use. It shows that high usage households achieve the greatest levels of peak demand reduction, with an average of -1.8% relative to the base case. Once again, this can be attributed to the fact that such households are likely to have access to a greater level of flexible demand than those using fewer appliances, thereby enabling them to respond to changes in energy price more significantly.

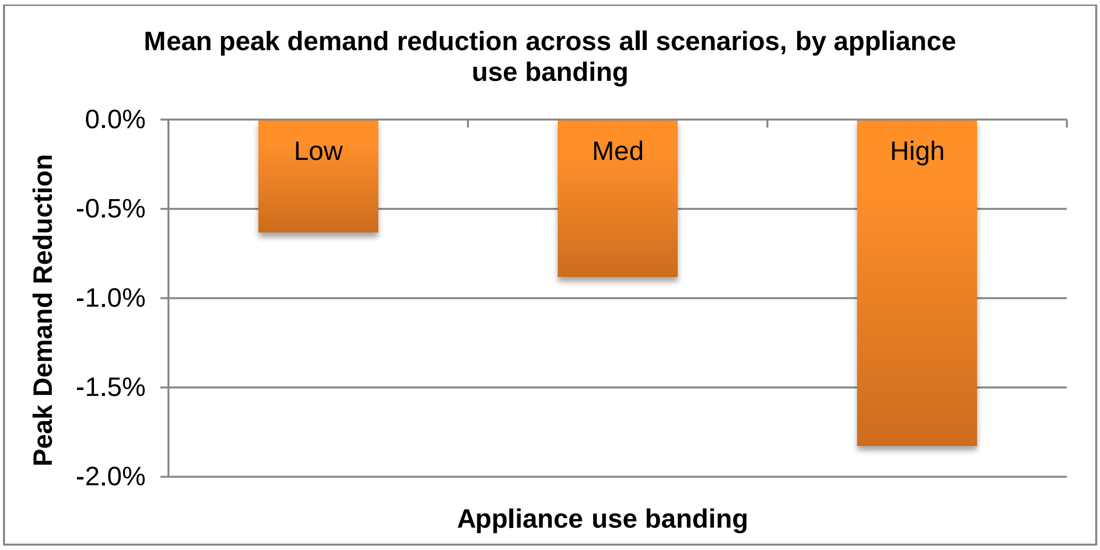


Figure 7-41 - Graph showing mean peak demand reduction according to appliance use banding.

7.4.4 Scope for free-rider effect

As discussed in Chapter 3, one of the primary concerns associated with exposing domestic consumers to energy price variation is the so-called “free-rider effect”, whereby unresponsive consumers receive the benefits from the responsiveness of others. Having already calculated the r_d values for each household and examined the impact of the variable pricing strategies upon household energy bills, it is possible to examine the extent to which the three strategies are susceptible to this effect.

In order to establish whether or not the three developed pricing strategies are susceptible to the free-rider effect, it was first necessary to determine which households could be deemed to be the most and least responsive. This was achieved by taking the mean r_d values of each household across all 36 scenarios. These values were then used to define three evenly sized groups, with the 33 households with the lowest average r_d values placed in the ‘High’ responsiveness group, the 33 with the highest average r_d values in the ‘Low’ responsiveness group and the remaining 34 households in the ‘Mid’ level responsiveness group. For all the households in each group, the mean percentage change in energy bill (relative to the flat rate pricing used as part of the base case) across all 36 scenarios was then calculated for each of the variable pricing strategies. The results of this process are shown in Table 7-13.

Table 7-13 - Mean change in household energy bills (relative to flat rate pricing) across all modelled scenarios, according to household responsiveness groupings.

	Low	Mid	High
VToU	3.9%	4.8%	3.1%
RTP	0.3%	1.6%	-0.2%
VCPP	-0.6%	-0.3%	-1.1%

This presents a number of key results when it comes to assessing the susceptibility of the developed variable pricing strategies to the free-rider effect. The fact that the mean change in energy bill for highly responsive consumers is lower than the 'Low' and 'Mid' responsiveness groups for all three pricing strategies indicates that the most responsive consumers are generally rewarded for their engagement. However, the mean bills for households who are least responsive are lower than those in the 'Mid' responsiveness group for all three strategies. This suggests a susceptibility to free-rider behaviour, in that the least responsive consumers see either less of an increase or more of a decrease in their energy bills compared to some households who engage in DR to a greater extent (in this case, those in the 'Mid' level responsiveness group).

7.5 Conclusions

This chapter has presented the results of the model simulation process and the performance metrics and indicators used to analyse them. The results show that the use of variable energy pricing in a notional SAHES can result in modest yet significant levels of DR both at a community and at a household level.

The three variable pricing strategies developed were all found to result in DR in 34 of the 36 scenarios simulated. As a result of this DR, the demand-supply match was increased in 30 of the 36 scenarios (83%). This shows the variable pricing strategies developed in the previous chapter to be effective, and capable of achieving their desired outcome in the vast majority of the varied conditions which occur throughout the year.

The analysis of the results was facilitated through the identification of 8 key performance metrics and indicators. 5 of these were applied at the community level, and measured the impact of variable pricing on the demand-supply match, the extent of community DR achieved, the number of responsive hours, community-wide DR engagement levels and the change in community level peak demand. A further 3 were applied at an individual household level: the extent of household DR; the impact of variable pricing on energy bills relative to the flat rate pricing base case; and the variation in results according to household appliance and elasticity bandings. Where appropriate, a further level of analysis was also been added by combining multiple performance metrics. This enabled a more detailed comparison of the results to take place.

Of the three variable strategies modelled, VToU was found to out-perform both RTP and VCPP across many key areas, including the overall impact upon the demand-supply match (as indicated by $r_{d:RES}$) and the extent of community-wide DR (as indicated by r_d). This result indicates that there is little benefit to be had from the additional stratification of energy pricing levels included in the RTP strategy.

VCPP was found to be the least effective of the three strategies, being outperformed by both RTP and VToU in many areas of analysis, with few exceptions. VCPP was also the only pricing strategy which failed to achieve DR, doing so on 2 occasions. This can be attributed to the limited extent to which the structure of the VCPP strategy reflects RES surplus/deficit levels when compared to the other two strategies.

When analysing the extent to which DR was engaged in, the use of r_d values alone was found to be insufficient. A more detailed analysis was facilitated by the inclusion of the number of ‘responsive hours’ which occurred over the course of each day modelled. This provides an indication of the number of hours each day in which the demand under variable pricing varies from the demand under the flat-rate pricing base case. The use of this additional metric helped minimise the potential for r_d values to under-represent changes in demand which are more spread out across the day i.e. more uniform in nature, and provides a more detailed account of the extent to which DR is engaged in.

The metrics and indicators used to quantify DR can also be usefully combined to give an impression of the effectiveness of DR under each of the pricing strategies. VToU was found to deliver the greatest improvement in the demand-supply match for each unit of change in community-wide demand. This is a significant result in that it conveys the effectiveness of each strategy at achieving the primary aim: improving the demand-supply match through DR.

At the household level, the examination of the extent of household DR has also been explored through the use of household r_d values. In addition, the examination of daily household profiles to illustrate the impact of DR upon household consumption has also helped to provide a link between the more abstract r_d values with actual consumer behaviour. This has helped identify the difference between low and high household r_d values, and the associated changes to consumption behaviour.

The examination of household energy bills under the variable pricing strategies has allowed comparisons to be drawn with the flat rate pricing applied as part of the base case model. Under maximum RES conditions, all three variable pricing strategies compare favourably with flat rate pricing when it comes to household bills. Conversely, under minimum RES conditions all three variable strategies are out-performed by flat rate pricing. These results reflect the fact that pricing reflects the overall level of RES surplus/deficit. Under mean RES conditions, flat rate pricing typically achieves mid-level performance in relation to the variable strategies. Across all of the modelled scenarios (twelve for each pricing strategy), the changes in household energy bills which resulted from the introduction of variable energy pricing were found to range from an increase of 10.5% to a decrease of 6.3%

relative to the flat-rate pricing base case. This shows the extents of the variation in household energy bills which would result from the introduction of variable pricing strategies such as those presented. However, it should also be stressed that the 12 scenarios which provided these figures do not reflect the full range of conditions which would occur over a full year. Therefore, bills in real-world applications are likely to vary more significantly.

Of the three household characteristics included in the mode, demand elasticity is the best indicator of likely daily bill changes, changes in household peak demand and r_d. This is therefore likely to be the most sensitive variable to changes, and therefore ideal for further analysis in the form of a sensitivity analysis.

The results suggest that the more appliances a household has, the more likely it is to avoid bill increases and the more able it is to reduce peak demand. The results also suggest that if high appliance usage was applied across all households, higher DR engagement rates are also likely. This has profound implications given the aforementioned trend in increasing appliance ownership, and suggests that as appliance use continues to increase, the suitability of households for domestic DR may also increase.

The need for the potential for free-rider behaviour to be addressed has also been identified, with the results indicating that all three of the variable pricing strategies are susceptible. Whilst the most responsive households benefit from the largest bill decreases and the smallest bill increases (a positive result), the least responsive households have also been found to benefit more than those with intermediate responsiveness levels.

Whilst the results provide some insight into how different consumer types would fare under variable energy pricing, they also serve to highlight the sensitivity of the model to a large number of key variables. Further detail, in the form of sensitivity analyses, is therefore clearly needed in order to better gauge the impact of these key variables, and to provide a clearer impression of the resilience of the developed model and the values it uses in these key areas, and therefore the applicability and transferability of its results. The next chapter will describe how these sensitivity analyses were designed and carried out, and will draw further conclusions as to the significance of these key variables.

7.6 References for Chapter 7

Born, F. (2001). *Aiding Renewable Energy Integration through Complementary Demand-Supply Matching*. University of Strathclyde. Retrieved from http://www.esru.strath.ac.uk/Documents/PhD/born_thesis.pdf

NREL. (n.d.). HOMER Energy. Retrieved from http://homerenergy.com/

Chapter 8: Sensitivity Analyses

8.1 Approach and Methodology

In the previous chapter, we saw how the introduction of variable energy pricing could successfully be used to promote DR amongst domestic consumers, and examined some of the resulting impacts upon households and on domestic energy consumption behaviour in general. However, given the complexity of the SAHES model, and the inherent uncertainty surrounding many of the variables it incorporates, a series of sensitivity analyses were deemed appropriate in order to:

- gauge the resilience of the results and of the pricing strategies modelled
- identify the variables which have the greatest impact upon the results
- account for some of the primary sources of uncertainty present in the model

In doing so, the sensitivity analyses featured in this chapter lend further depth to the results and provide some indication as to the likely resilience of the developed model and the results it yields.

8.1.1 Experimental design

In order to ensure that the sensitivity analyses contribute meaningfully to the results obtained in the preliminary modelling stage described in the last chapter, it is necessary to first determine which variables to subject to change. These variables should consist of those which have the highest level of inherent uncertainty and those which are most likely to be subject to change in real world applications. The variables included can be broadly categorised as those which relate to energy demand and those which relate to energy supply. A third category can also be added, which relates to how variable pricing is applied. One variable from each of these categories was selected for sensitivity analysis. The selected variables are:

1. RES intermittency
2. consumer price elasticity of demand
3. price ratio: the ratio between minimum and maximum pricing levels which occur

For each of these three variables, a range of incremental alternative values was selected which represent the range of variation which can be deemed to be ‘reasonably likely’ to exist in real world applications. Figure 8-1 shows the variables selected for inclusion in the sensitivity analyses, and outlines the structure of the remainder of this chapter.

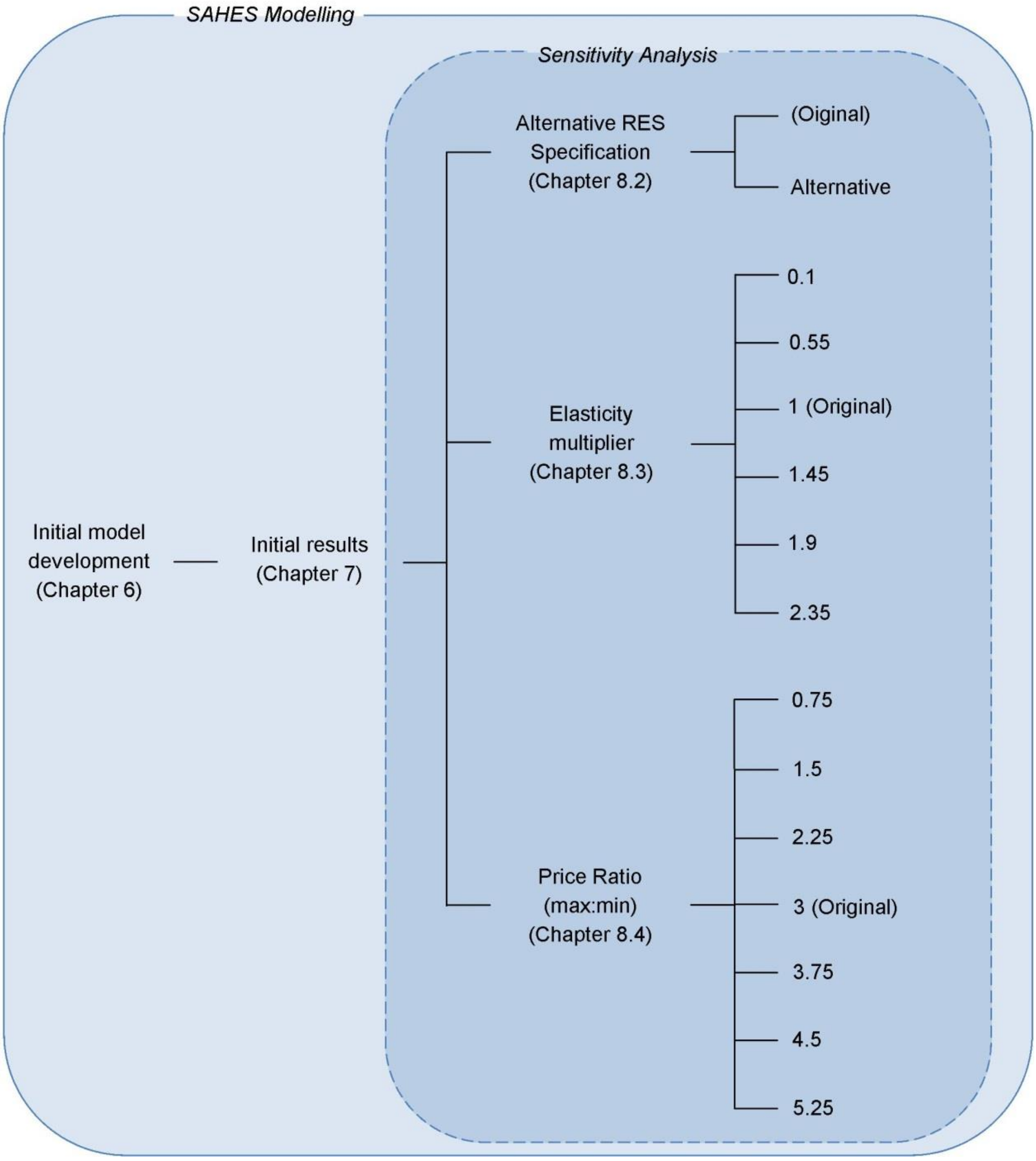


Figure 8-1 - Diagram showing the variables subject to sensitivity analysis, and the range of alternative scenarios modelled.

In designing the sensitivity analyses, it is also necessary to account for the simulation time required for each individual iteration. The SAHES model takes around 200 seconds to simulate each combination of pricing strategy, season and RES conditions, with manual data input being required in each instance. This gives a total time of approximately 2 hours for every suite of 36 simulations to be run (not including the time required for manual data input). Variables must also be altered incrementally and simulated on an individual basis rather than a combinatorial one, in order to allow the impact of each change to be made clear.

Given the number of iterations included in the sensitivity analyses, it was also considered prudent to limit the number of results indicators and performance metrics included in the results analysis and discussion. Focussing on a select number of key results indicators allowed meaningful conclusions to be drawn from a large volume of results data.

8.2 RES Intermittency

Being arguably the most inherently variable phenomena featured in the model - and also that which was subjected to the greatest degree of approximation/aggregation - the variation in the supply from RES can be seen as having the greatest scope for variation, and is therefore in need of further investigation. The RES profiles found in SAHES are highly site specific, with the choice and sizing of RES technologies being influenced by a range of constraints such as available resources and other site constraints, local climatic conditions, project budget and funding mechanisms, planning restrictions/regulatory issues and local attitudes. The majority of these factors cannot be meaningfully represented in the model developed in this study. Indeed, doing so would introduce a degree of specificity that would limit the extent to which the model itself could be deemed representative of SAHES. However, the RES profiles which result from the technological specification *can* be varied within the model, and the impacts examined.

8.2.1 Alternative scenario development

The results presented in the previous chapter attempt to account for the variability of RES by encompassing the minimum and maximum supply days which occur throughout the four seasons. However, this is limited to the specific system design of the SAHES itself i.e. the specific forms and sizes of the energy generation and storage technologies specified. Running the model under an alternative specification therefore facilitates further understanding of the extent to which results are sensitive to RES and storage specification.

Choosing one or more alternative specifications to model is difficult, as it is necessary to maintain adherence to the constraints developed as part of the original model development, in order to maintain the comparability of results e.g. demand characteristics, climate data etc. In addition, the method used to size the SAHES itself (HOMER) must also remain constant in order to ensure a meaningful comparison.

In order to provide a meaningful and significant variation to the fundamental characteristics of the RES profile i.e. the 'shape' of the profile, it was decided to focus specifically on altering the intermittency associated with the RES technology specification i.e. the amount of generation which is inherently unpredictable and variable. This was achieved through the removal of hydro power from the list of potential energy sources which were available for selection in the HOMER model. Not only did this alter the number and type of technologies specified, but it also increased the intermittency associated with the energy supply profile by removing a comparatively stable generation source (in the form of hydro power) from the model, thereby increasing the system's reliance on other more intermittent sources, and on diesel generation. This has specific relevance to the SAHES model because the intermittency of the RES has a direct impact on pricing levels. This method also ensures that HOMER's technological selection and sizing methodology is allowed to function without alteration, thereby ensuring a viable specification. Table 8-1 shows that the demand characteristics used to generate the alternative specification were the same as those used in the original (base case) model.

Table 8-1 - Comparison of the original modelled SAHES specification and the alternative specification.

Consumption Characteristics:	Original	Alternative
Community consumption (kWh/day)	1654	1654
Peak demand (kW)	354	354
Load Factor	0.195	0.195
Mean demand (kW)	68.9	68.9

A comparison between the original system RES specification and the resulting alternative specification is provided in Table 8-2.

Table 8-2 - Comparison of the original SAHES specification with the alternative specification.

SAHES Specification:	Original	Alternative
Photovoltaic array (kWp)	25	15
Wind energy (total rated output, kW)	325	800
Battery storage (nominal capacity, kWh)	2432	3330
Hydro (kW)	49.7	0
Converter (kW)	180	200
Diesel Generation:		
Plant size (kW)	180	200
Annual hours of operation	292	428
Diesel consumption (litres/year)	9760	16190

As shown in Table 8-2, the shortfall in RES created by the removal of hydro power capacity in the alternative specification was addressed by increasing wind generation capacity significantly (by 146%) as well as increasing storage capacity (by 37%) and the size of the diesel-fuelled back-up generation capacity (by 11%). The size of the photovoltaic array specified was also reduced by 40% in the alternative scenario, from 25 kWp to 15 kWp.

These changes in the generation mix were selected by the HOMER model as the most cost-effective response to the loss of generation caused by the removal of hydro power from the list of available generation technologies. The resulting alternative specification forecast a 66% increase in diesel consumption and a 104% increase in the total rated RES capacity relative to the original specification. This effectively illustrates the impact of increased reliance on intermittent forms of renewable generation.

8.2.2 Impact on RES profiles

The impact of these changes upon the RES profiles is shown in Figure 8-2 to Figure 8-5, which compare the RES profiles under the alternative specification with the original profiles used to generate the model results presented in Chapter 7.

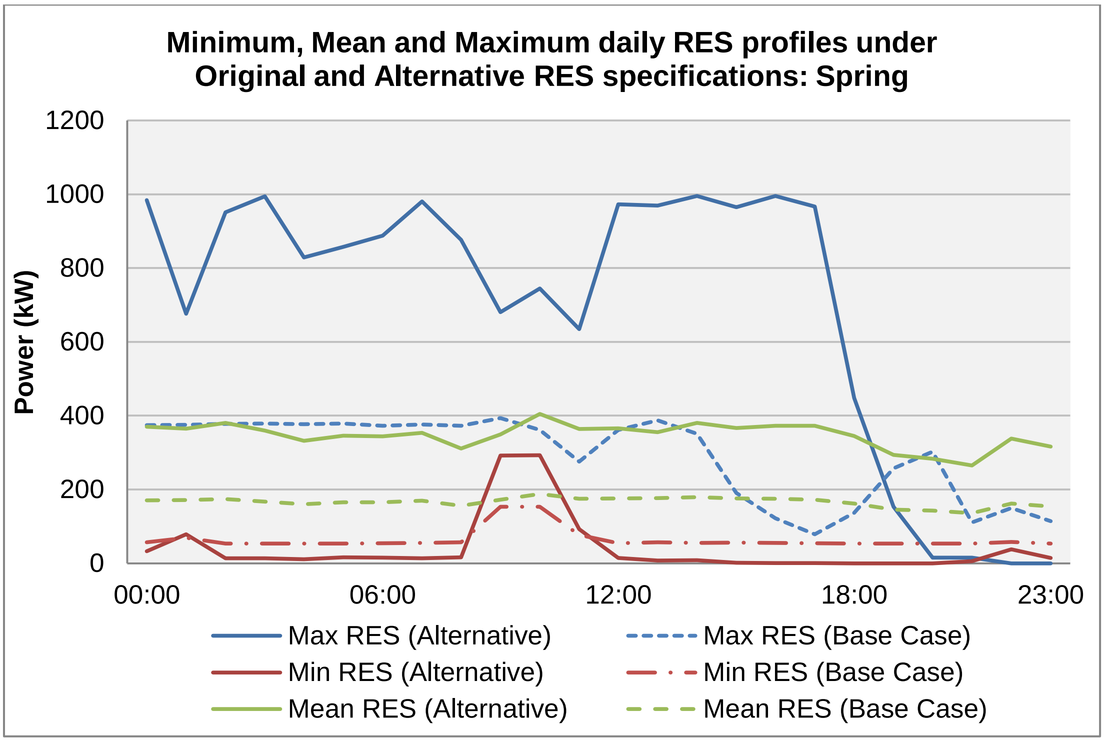


Figure 8-2 - Graph comparing spring day minimum, mean and maximum RES profiles under the alternative RES specification with those from the original specification.

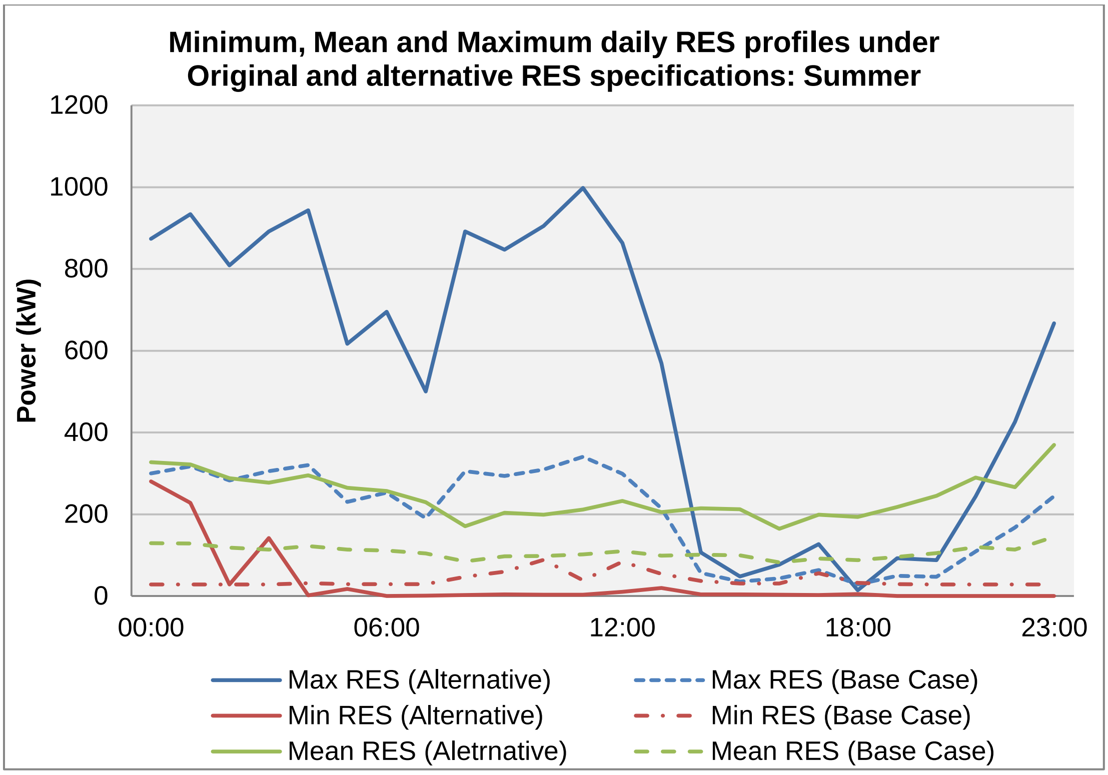


Figure 8-3 - Graph comparing summer day minimum, mean and maximum RES profiles under the alternative RES specification with those from the original specification.

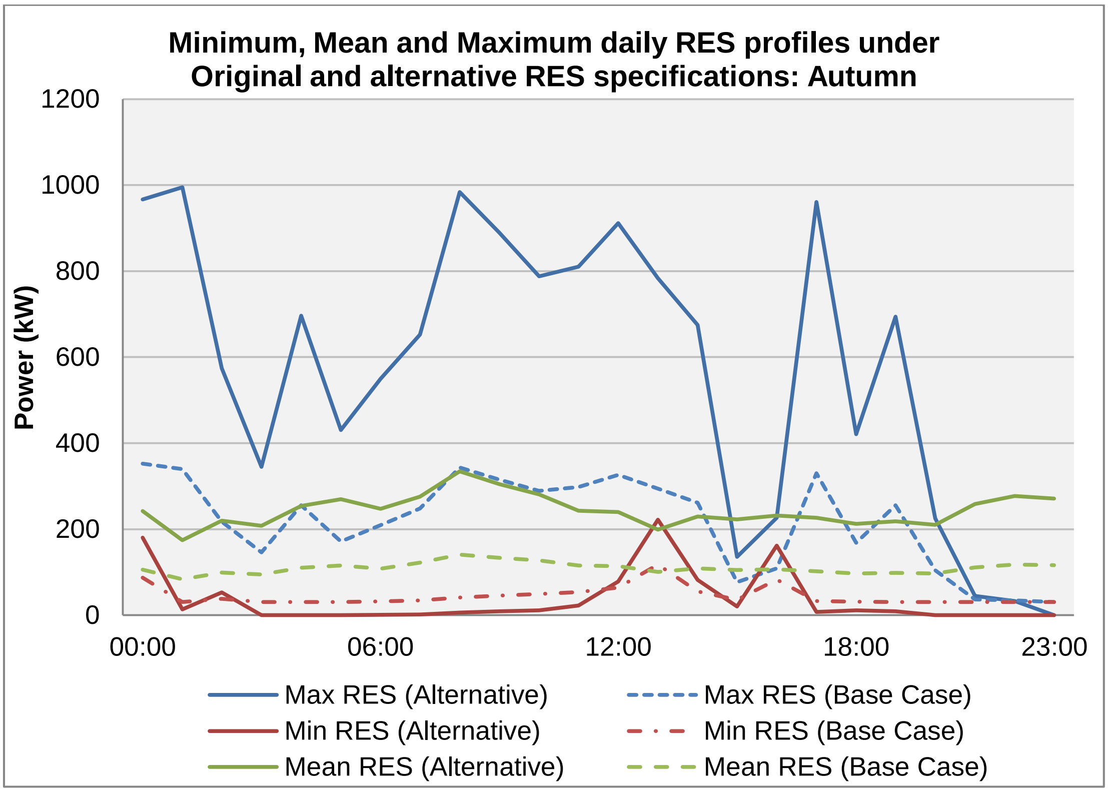


Figure 8-4 - Graph comparing autumn day minimum, mean and maximum RES profiles under the alternative RES specification with those from the original specification.

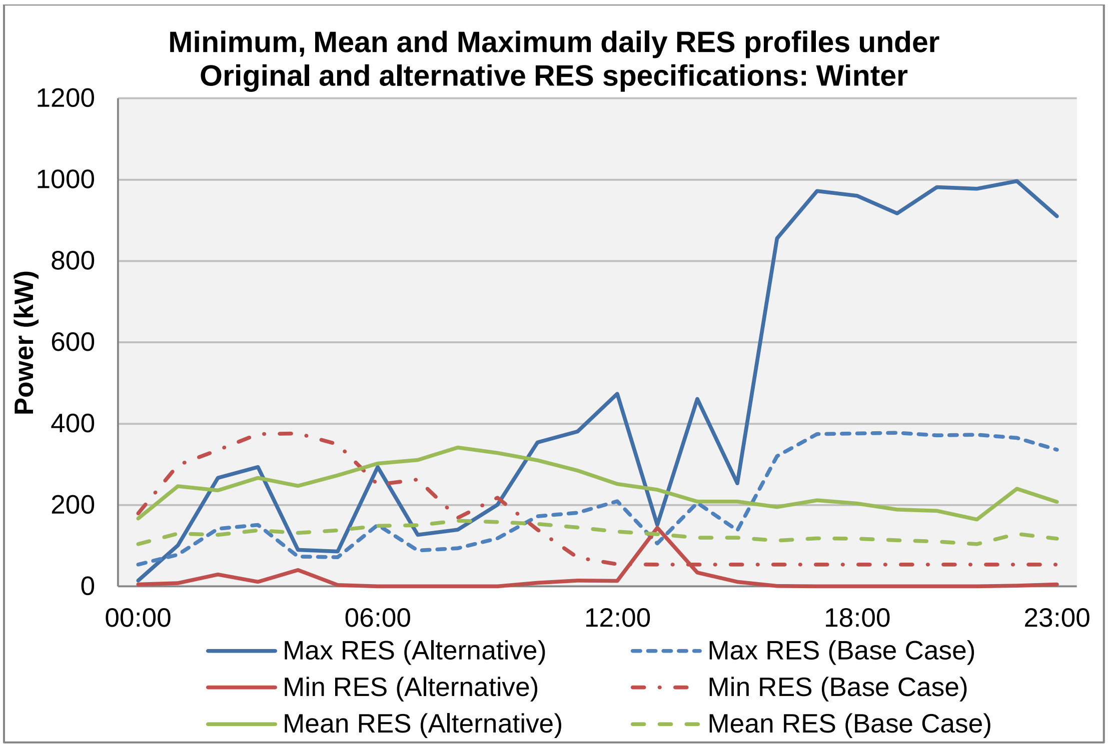


Figure 8-5 - Graph comparing winter day minimum, mean and maximum RES profiles under the alternative RES specification with those from the original specification.

These graphs illustrate the extent to which the RES profiles change under the alternative specification. Most notable is the marked increase in overall RES levels during maximum RES conditions, with peak RES levels of around 400kW under the original specification being far surpassed, to around 1MW under the alternative specification. Since demand levels remain the same, this variation partially accounts for the significant increase in storage capacity specified in the alternative model.

8.2.3 Impact on energy pricing

Despite the significant variation in renewable energy supply resulting from the alternative system specification, it is worth reiterating that the developed pricing strategies are designed to ensure that the mean energy price across each month of the year remains the same, thus ensuring that all ranges of RES surplus/deficit values are taken into account. For this reason, levels of renewable energy surplus of a much greater magnitude will not necessarily translate into much lower energy prices.

In order to understand how changes in RES specification ultimately impacts upon the levels of DR achieved under a given scenario, it is useful to consider how the impact of the variation permeates through the various stages of the model itself. Consider the example of the VToU pricing strategy, under minimum RES conditions during the spring seasonal day. Under the original, less intermittent RES specification, the range of values represented by each of the three pricing points is relatively narrow (from a RES deficit of 207kW to a surplus of 371kW, giving a total range of 578kW). Under the alternative RES specification, which includes larger proportions of intermittent wind energy, the range of values for each pricing point is far greater (from a deficit of 254kW to a surplus of 986kW, giving a total range of 1240kW). This means that the pricing algorithm is more sensitive to fluctuations in RES surplus/deficit values under the original specification. This is illustrated by Figure 8-6, which shows the RES deficit/surplus ranges for both specifications.

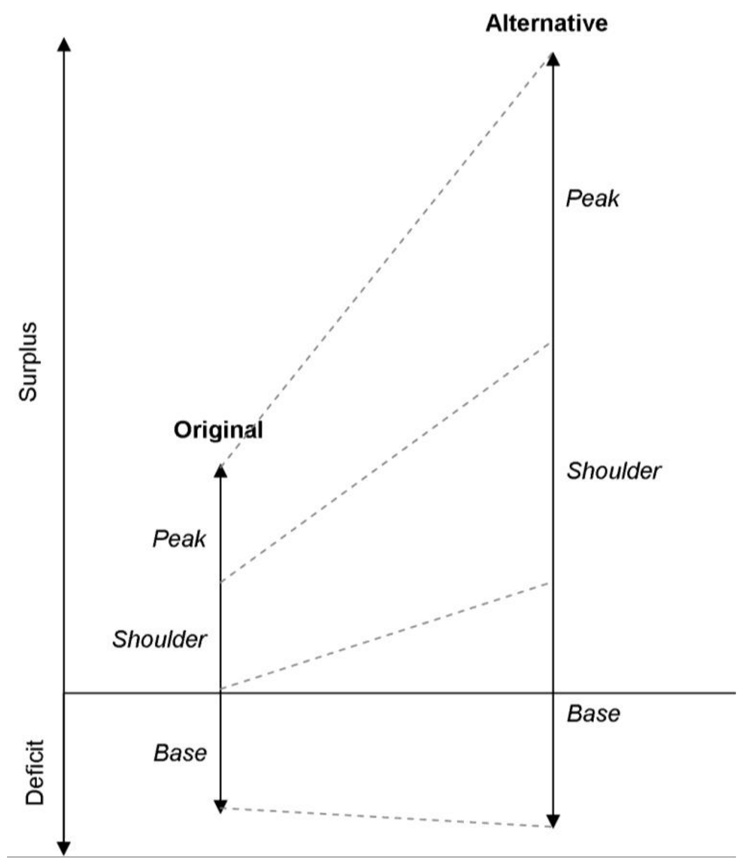


Figure 8-6 - Illustration of the increase in the RES surplus/deficit range which occurs under the alternative RES specification (VToU - Spring).

Figure 8-7 shows the VToU pricing levels for each strategy during the scenario in question. This reflects the increased sensitivity of the pricing level under the original RES specification, with 8 changes in price occurring over the course of the day, as opposed to just 2 for the alternative RES specification. As a result, there is less opportunity for consumers to make cost savings by engaging in DR. This is reflected in the community-wide r_d values, with the original RES specification achieving a greater level of DR (0.991) than the alternative specification (0.995).

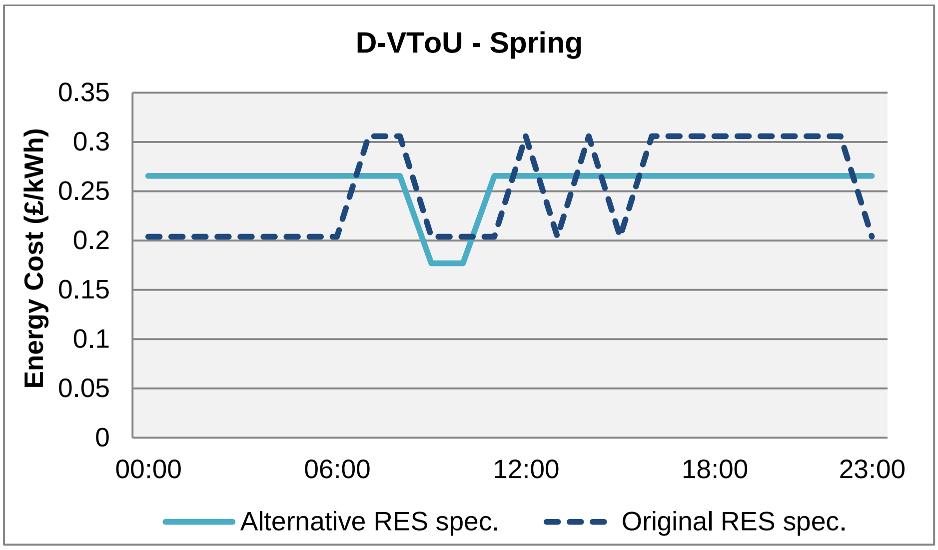


Figure 8-7 - Graph showing the price of energy under VToU during the spring seasonal day under both the original and the alternative RES specification.

Figure 8-7 also shows that the change in RES specification not only changes the shape of the pricing profile, but also the pricing levels themselves, resulting in higher pricing levels for both maximum and minimum prices under the alternative specification. As discussed above, this stems from the fact that monthly projected minimum and maximum RES deficit values i.e. the RES deficit/surplus range, provide the basis for the pricing levels used.

Despite the small difference in r_d values the community-wide demand profiles, as shown in Figure 8-8 and Figure 8-9, clearly illustrate the greater DR levels achieved under the original specification, as well as the aforementioned variation in RES surplus/deficit value ranges.

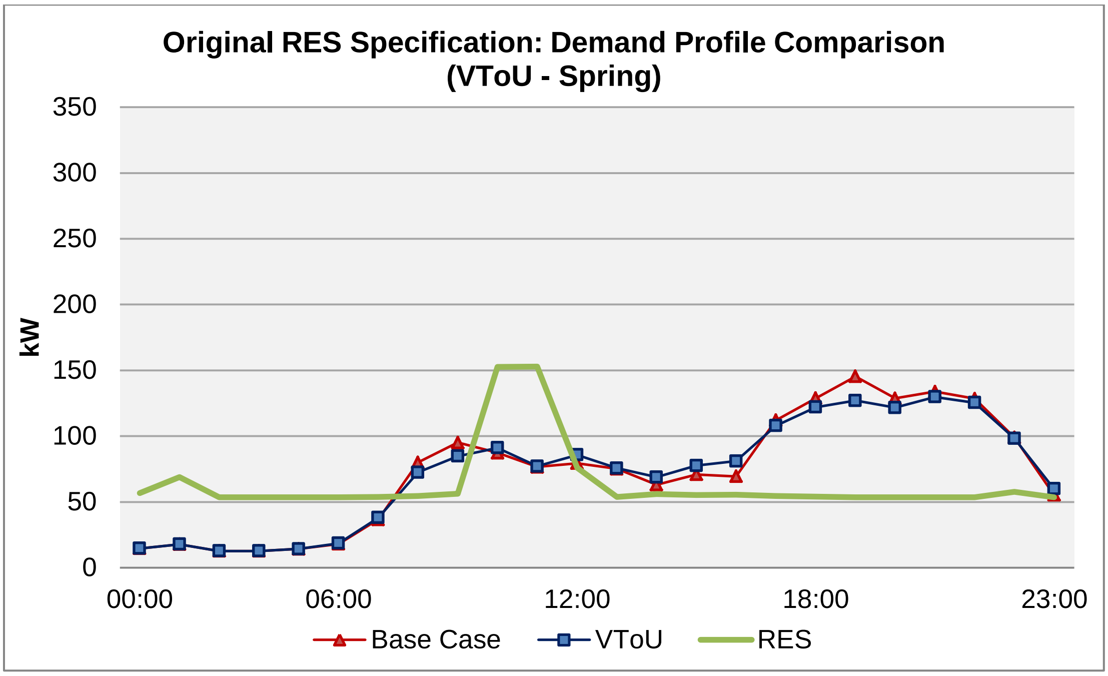


Figure 8-8 - Graph showing the community demand profile for the spring seasonal day under flat rate pricing and VToU. Also shown is the RES profile (in green) associated with the original RES specification.

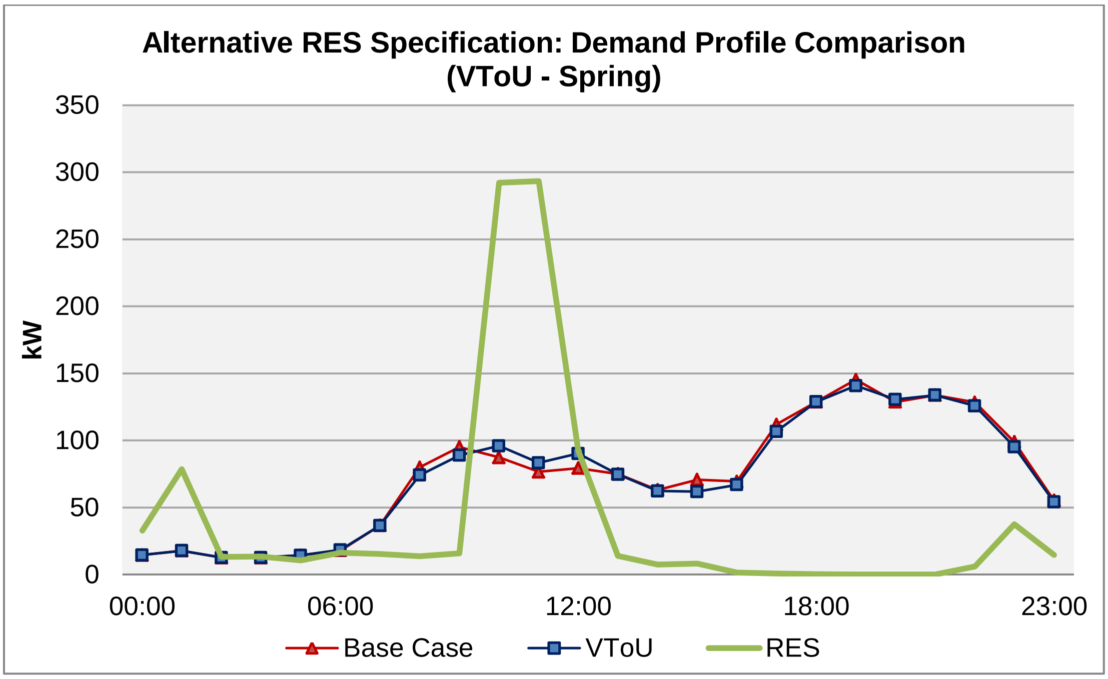


Figure 8-9 - Graph showing the community demand profile for the spring seasonal day under flat rate pricing and VToU. Also shown is the RES profile (in green) associated with the alternative RES specification.

This is also true of the VCPP strategy, though less markedly so given that all periods of projected RES surplus are assigned the same price regardless of the magnitude of the surplus itself.

Another effect of the change in RES specification (as illustrated by Figure 8-2 to Figure 8-5, above) is the reduction in the base level of generation which results from the removal of a comparatively constant source of supply in the form of hydro power. As a result, the latter part of the minimum RES winter day sees generation fall to a minimum of less than 5kW for a period of 8 hours. This justifies the aforementioned increase in energy storage and/or back-up generation in the form of diesel generator(s) under the alternative RES specification.

Figure 8-10 to Figure 8-12 show the maximum projected monthly RES surplus and deficit values used by the variable pricing strategies to set their respective pricing increments. As shown in Figure 8-10, the maximum projected deficit values vary only slightly, with monthly values increasing by between 12% (Autumn) and 23% (Spring) under the alternative scenario. Again, this can largely be attributed to the loss of the comparatively consistent levels of generation supplied by hydro power.

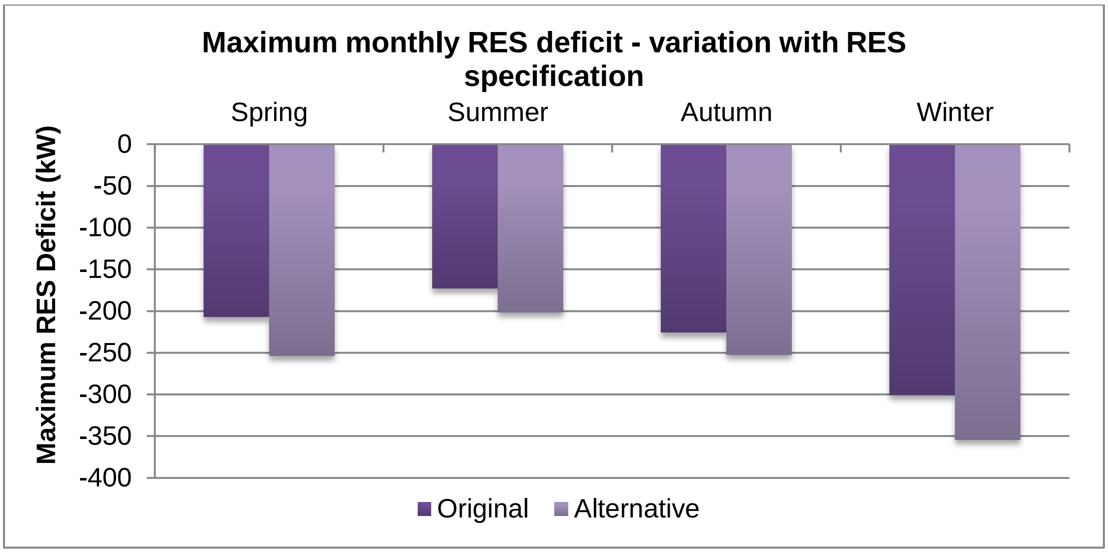


Figure 8-10 - Graph showing monthly RES deficit values under original and alternative RES specifications.

The changes in RES surplus values, as shown in Figure 8-11, are much greater due to the need for increased levels of intermittent sources - namely wind power in this case. Here, values under the alternative RES specification show an increase of between 166% (Spring and Winter) and 190% (Autumn) relative to the base case specification.

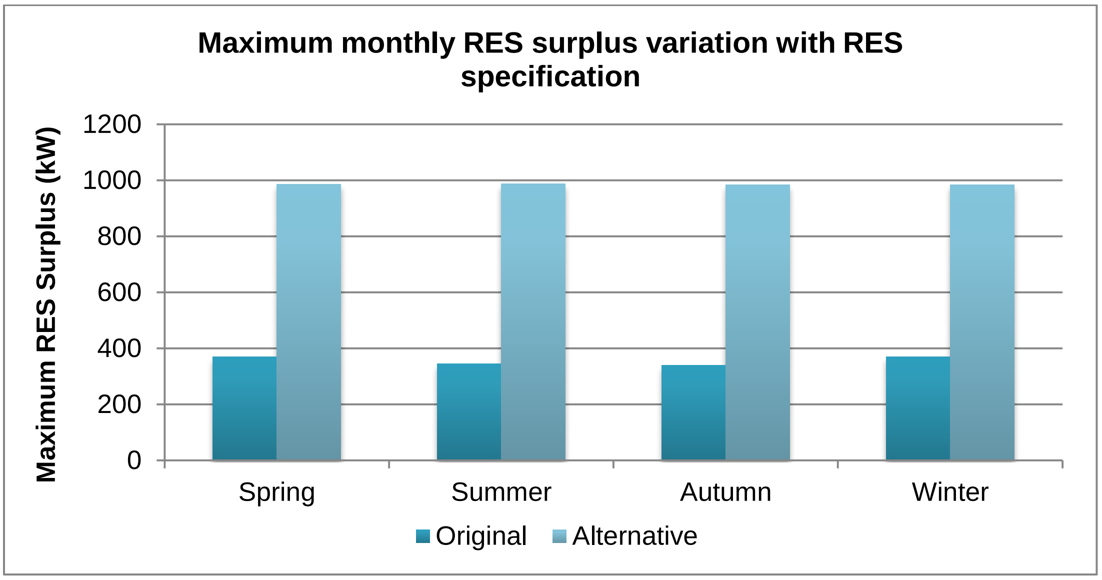


Figure 8-11 - Graph showing monthly RES surplus values under original and alternative RES specifications.

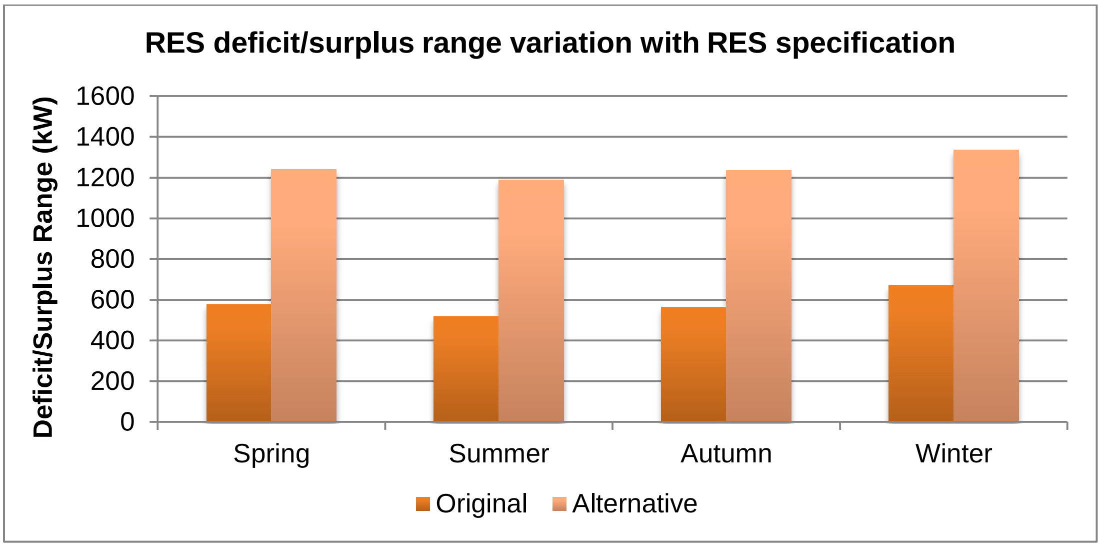


Figure 8-12 - Graph showing monthly RES deficit/surplus ranges under original and alternative RES specifications.

However, despite the often large variations in the amount of renewable energy generated by the two RES specifications, the difference is not always translated into changes in pricing profiles. This is due primarily to the fact that the profiles account for the possible range of RES values, with pricing points being allocated accordingly. As a result, even sizeable changes in RES can result in similar pricing profiles. This is clearly demonstrated in Figure 8-13, which shows the strong correlation between the RTP pricing profiles for maximum RES conditions in Summer under both RES specifications, despite the fact that the total RES under the original specification was 4810.6 kWh, and the RES under the alternative specification was 13230.8 kWh, an increase of 175%. The resulting difference in RES surplus is shown in Figure 8-14.

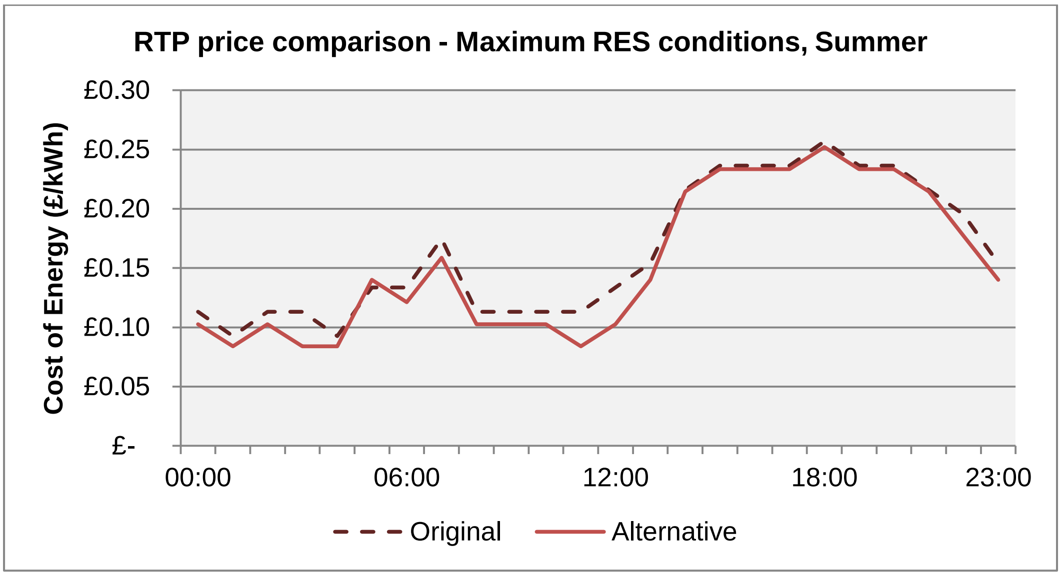


Figure 8-13 - Comparison of RTP pricing under original and alternative RES specification, during maximum RES conditions in Summer.

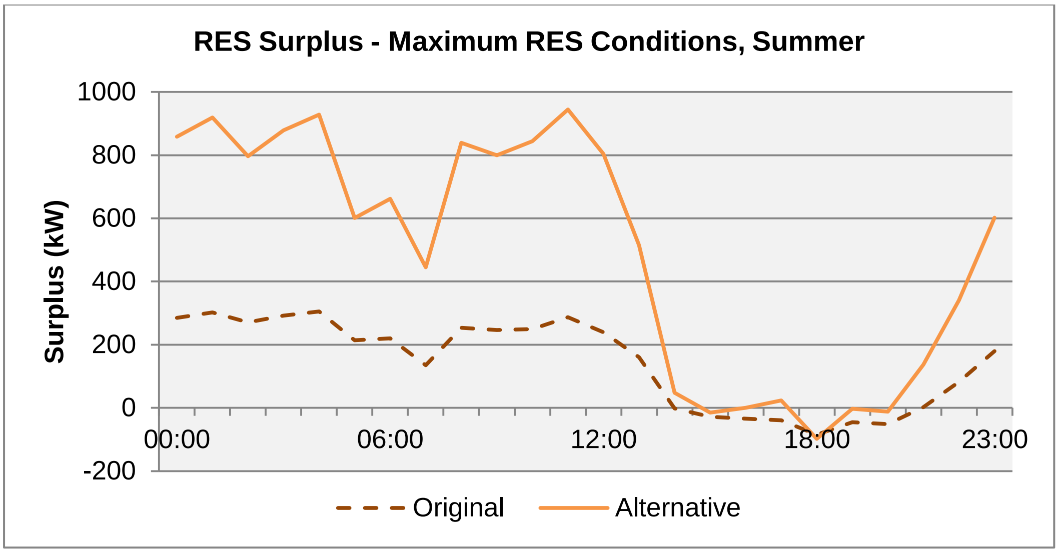


Figure 8-14 - Comparison of the RES surplus which occurs under maximum RES conditions in Summer, under both RES specifications.

The fact that the design of the pricing strategies limits the potential for price variation can in this instance be seen as being both an advantage and a limitation. While the scale of the RES surplus which occurs under the alternative RES specification could be used to further reduce the price of energy to consumers, this would represent an increased level of exposure to risk, as the opposite could (and does) occur under *minimum* RES conditions. By limiting this exposure, the effect of the magnitude of RES surplus/deficit is lessened dramatically.

8.2.4 Community level results

With such fundamental changes being made to the RES profile, the levels of DR achieved under the alternative specification can be expected to differ from the original specification. The extent to which the impacts of the change in RES specification differ provide an indication of how sensitive the variable pricing strategies are to changes in RES characteristics, and therefore how resilient such an approach is likely to be in diverse real world applications. The focus of the results analysis in this case is therefore placed on examining the differences that exist between the results of both RES specifications.

However, the nature of the changes to the model parameters also limited the extent to which the results of both the original and alternative RES specification could be directly compared. This analysis therefore focuses on the impact of the alternative RES scenario on the resulting $r_{d:RES}$ changes, which is again regarded as the basic indicator of the effectiveness of DR given the primary aim of improving the demand-supply match. The community-wide levels of DR which occur under each RES specification, measured by r_d values, are also examined.

Table 8-3 to Table 8-5 compare the community-wide r_d values under both RES specifications for all of the modelled scenarios. The change in r_d varies with each scenario, from a decrease of 0.014 (under VToU during the winter seasonal day, in minimum RES conditions) to an increase of 0.023 (under RTP during the spring seasonal day, in maximum RES conditions) relative to the levels achieved under the original RES specification.

Table 8-3 - Comparison of changes in community-wide r_d under original and alternative minimum RES specifications.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	0.991	0.995	0.998	0.999	0.997	0.984
Summer	0.996	1.000	0.998	0.998	0.997	0.997
Autumn	0.986	1.000	0.995	0.992	0.985	0.983
Winter	0.981	1.000	0.997	0.990	0.993	0.991
Mean	0.988	0.999	0.997	0.995	0.993	0.989
Range	0.015	0.005	0.003	0.009	0.012	0.014

Table 8-4 - Comparison of changes in community-wide r_d under original and alternative mean RES specifications.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	1.000	0.993	0.989	0.999	1.000	1.000
Summer	0.998	0.996	0.999	0.996	0.999	1.000
Autumn	0.987	0.987	0.993	0.997	0.990	1.000
Winter	1.000	0.986	0.986	0.994	0.988	1.000
Mean	0.996	0.990	0.992	0.997	0.994	1.000
Range	0.013	0.009	0.013	0.005	0.012	0.000

Table 8-5 - Comparison of changes in community-wide r_d under original and alternative maximum RES specifications.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	0.988	0.975	0.976	0.999	0.996	0.996
Summer	0.986	0.981	0.993	0.993	0.994	0.998
Autumn	0.994	0.987	0.994	0.993	0.995	0.999
Winter	0.997	0.997	0.994	0.996	1.000	1.000
Mean	0.991	0.985	0.989	0.995	0.996	0.998
Range	0.011	0.021	0.019	0.007	0.006	0.004

Across all of the 12 scenarios, VToU achieves greater levels of DR during mean and maximum RES conditions under the alternative specification, and less during minimum RES conditions. Conversely, both RTP and VCPP perform worse under mean and maximum RES conditions under the alternative specification and better under minimum RES conditions.

Perhaps the most notable result is that of the VCPP pricing strategy under mean RES conditions, where no DR occurs in any of the four seasonal days simulated. This is due to the fact that the pricing strategy sets no pricing variation in these circumstances. This suggests that the bandings for each price point span too large a range, meaning that fluctuations in supply which resulted in price variation under the original specification fail to do so under the alternative RES specification. As with RTP, average r_d values are lower than under the original specification under minimum RES conditions and higher under maximum RES conditions. However, the differences are less pronounced.

The changes in $r_{d:RES}$ which occur under the alternative RES scenario relative to the base case are compared with the values from the original model results in Table 8-6 to

Table 8-8.

Table 8-6 - Comparison of changes in $r_{d:RES}$ under original and alternative RES specifications during minimum RES conditions.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	0.03	0.07	-0.02	-0.03	0.02	0.00
Summer	0.05	0.00	0.02	0.00	0.03	0.00
Autumn	0.08	0.00	0.03	-0.01	0.01	0.01
Winter	0.05	0.00	0.03	-0.02	0.02	0.00
Mean	0.05	0.02	0.01	-0.01	0.02	0.00
Range	0.05	0.07	0.05	0.03	0.01	0.01

Table 8-7 - Comparison of changes in $r_{d:RES}$ under original and alternative RES specifications during mean RES conditions.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	0.00	0.07	0.04	-0.01	0.00	0.00
Summer	0.01	-0.01	-0.02	0.01	0.01	0.00
Autumn	0.04	0.05	0.02	-0.01	0.03	0.00
Winter	0.00	0.07	0.00	0.04	0.01	0.00
Mean	0.01	0.04	0.01	0.01	0.01	0.00
Range	0.04	0.07	0.07	0.05	0.03	0.00

Table 8-8 - Comparison of changes in $r_{d:RES}$ under base case and alternative specifications during maximum RES conditions.

	VToU		RTP		VCPP	
	Original	Alternative	Original	Alternative	Original	Alternative
Spring	0.08	0.13	0.07	0.00	0.02	0.04
Summer	0.06	0.05	0.03	0.03	0.02	0.01
Autumn	0.03	0.00	0.02	-0.01	0.01	0.00
Winter	0.01	0.02	0.03	0.03	0.00	0.00
Mean	0.04	0.05	0.04	0.01	0.01	0.01
Range	0.07	0.13	0.05	0.04	0.02	0.04

These tables show that the variation in $r_{d:RES}$ values which occur under both RES specifications varies according to the RES conditions which occur during the different seasons of the year. RTP is found to vary the least of all the three strategies, a result which reflects the fact that it is less affected by the loss of accuracy suffered by the other strategies due to increased deficit/surplus ranges, thanks to the greater number of pricing increments it incorporates. Generally, the original RES specification results in greater changes in $r_{d:RES}$ than the alternative.

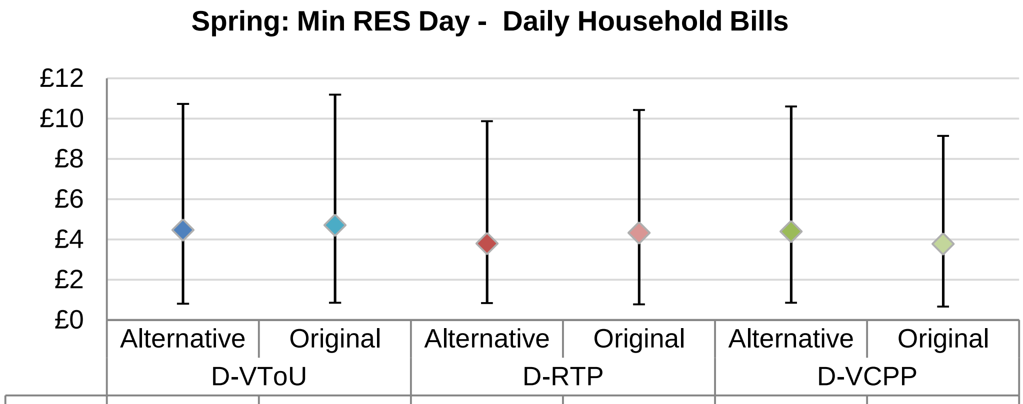
VCPP achieves noticeably less impact upon $r_{d:RES}$ values under the alternative specification - failing to achieve any significant impact in 9 of the 12 simulations. A significant proportion of this can be accounted for by the fact that no price variation occurs under VCPP during mean RES conditions, but even under minimum RES conditions - when the original specification achieved improvements in the demand-supply match during all 4 seasonal days - the alternative scenario returns just one change (which is equal to that achieved under the original specification).

8.2.5 Household level results

At a household level, the main indicators of interest are the differences in household DR (r_d) and the impact of the alternative RES specification upon household energy bills.

Since the alternative RES specification has an impact on the pricing levels resulting under each of the three pricing strategies (as discussed in 8.2.3), it stands to reason that household energy bills will also be affected.

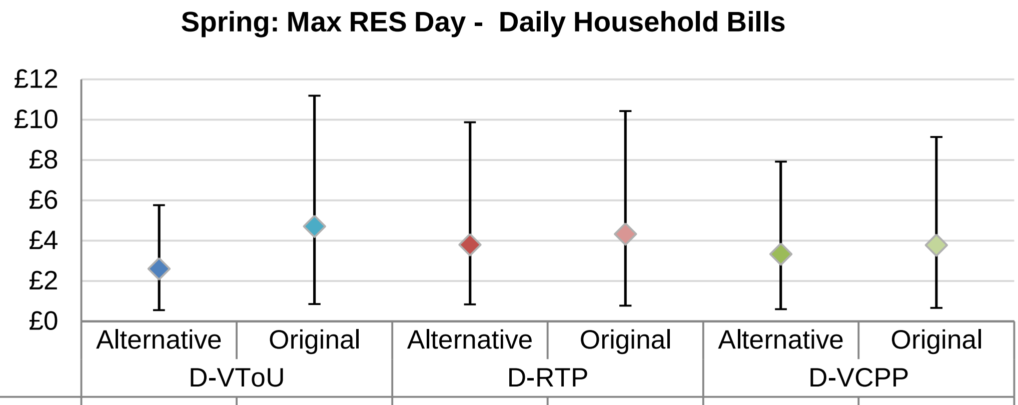
Under minimum supply conditions, VCPP is the only pricing strategy which sees an increase in household bills when compared to the original RES specification in all four of the seasonal days. This is due to scale of the price increase implemented by the VCPP strategy during times of RES deficit. For VToU and RTP, the alternative RES scenario results compare favourably with those of the original RES specification, in that the minimum, mean and maximum household bills are all less. This is shown in Figure 8-15.



	Alternative	Original	Alternative	Original	Alternative	Original
	D-VToU		D-RTP		D-VCPP	
Max	£10.73	£11.18	£9.87	£10.43	£10.60	£9.13
Mean	£4.46	£4.70	£3.79	£4.32	£4.39	£3.77
Min	£0.81	£0.85	£0.83	£0.77	£0.84	£0.67

Figure 8-15 - Range of household energy bills under minimum RES conditions during the Spring seasonal day, for both original and alternative RES specifications.

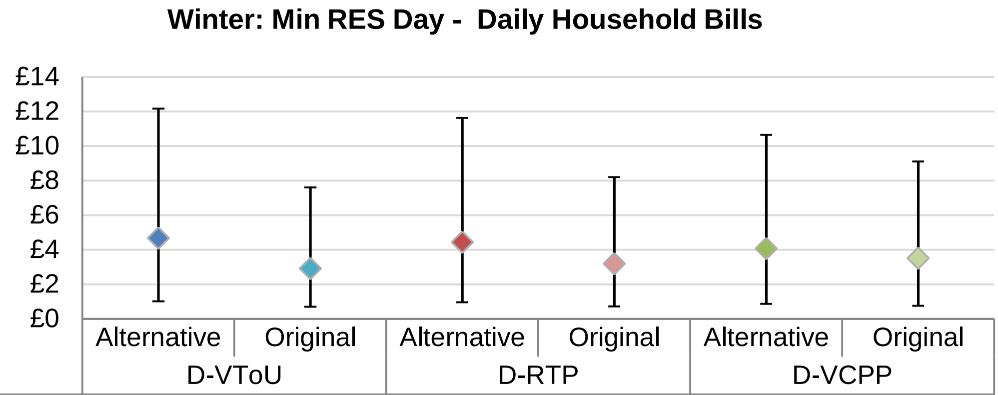
As expected, household bills which occur during maximum RES conditions are lower in the alternative RES scenario, due to the fact that the surplus experienced during such conditions lasts longer than in the original scenario thanks to the increase in wind generation capacity. This effect can be seen in Figure 8-16, which compares the bills under all three pricing strategies on the maximum RES day in Spring, for both the original and alternative RES specifications.



	D-VToU Alternative	D-VToU Original	D-RTP Alternative	D-RTP Original	D-VCPP Alternative	D-VCPP Original
Max	£5.76	£11.18	£9.87	£10.43	£7.92	£9.13
Mean	£2.60	£4.70	£3.79	£4.32	£3.33	£3.77
Min	£0.55	£0.85	£0.83	£0.77	£0.60	£0.67

Figure 8-16 - Range of household energy bills under maximum RES conditions during the Spring seasonal day, for both original and alternative RES specifications.

An interesting case is provided under minimum RES conditions during winter, the results of which are shown in Figure 8-17. Under the original RES specification, the VToU strategy resulted in the lowest bills, followed by RTP, with VCPP resulting in the highest. Under the alternative scenario however, this order is reversed.



	D-VToU		D-RTP		D-VCPP	
	Alternative	Original	Alternative	Original	Alternative	Original
Max	£12.16	£7.60	£11.62	£8.20	£10.65	£9.09
Mean	£4.67	£2.91	£4.43	£3.19	£4.06	£3.51
Min	£1.01	£0.70	£0.95	£0.72	£0.87	£0.75

Figure 8-17 - Range of household energy bills under minimum RES conditions during the Winter seasonal day, for both original and alternative RES specifications.

In order to understand the causes of these variations, it is necessary to examine the results in more detail. Figure 8-18 shows the variation in household energy bills which results from the change in RES specification, under VToU pricing during minimum RES conditions on the spring seasonal day. Across all 100 households, energy bills are found to increase by 5.0% less than under the original specification, as indicated by the 10-point moving average. This reduction occurs despite the community as a whole consuming more energy (an increase of 0.4%) and engaging in less DR (with a r_d value of 0.995 compared to 0.991) than under the original RES specification. This shows that there is less DR occurring under the alternative specification.

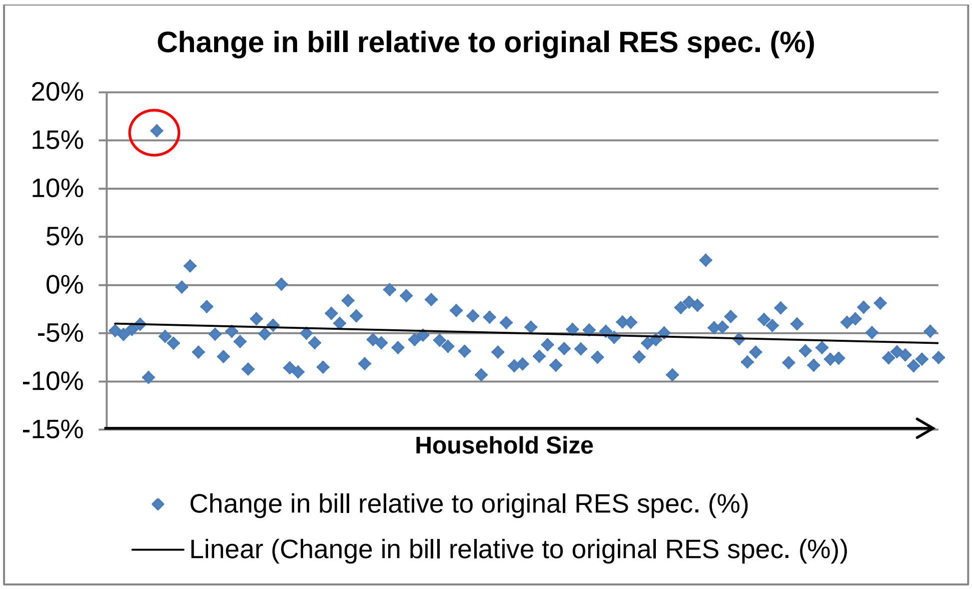


Figure 8-18 - Graph showing the change in household energy bills caused by the change in RES specification, under the VToU pricing strategy during maximum RES conditions during the spring seasonal day.

Figure 8-18 also shows a marginal decrease in the spread of the results as household numbers increase. Since household results are plotted in order of increasing size (number of permanent occupants), the impact upon smaller households (towards the left hand side of the graph) is greater than on larger households. This reflects the fact that the potential impact of an individual DR action is greater in smaller households, as the load in question is more likely to represent a greater proportion of the household's total daily consumption. This is also reflected in Table 8-9, which shows the average impact on energy bills for the day in question for each household size.

The outlying data point shown (circled in red) which sees a bill increase of 16% under the alternative RES specification relative to the original, serves to underline this result. This outlier is caused by the fact that under the scenario in question, a significant DR action which occurred under the first RES specification - namely a load curtailment which resulted in a decrease in total daily consumption of 12% - did not occur under the alternative specification.

Table 8-9- Table showing the variation in impact on energy bills caused by variation in the RES specification, according to household size.

Household Size	Percentage change in bill relative to original RES spec.
1	-3.2%
2	-5.4%
3	-4.3%
4	-6.0%
5	-6.7%

As touched upon above, the change in RES specification can have an effect on the levels of DR which take place, due to the impact upon energy pricing levels and variations. As such, household r_d values also show similar, limited, variation.

8.2.6 Results discussion

The results indicate that all three of the variable pricing strategies were sensitive to changes in RES specification. This sensitivity was also translated into the simulation results, with variations in the levels of DR achieved present in the vast majority of the scenarios modelled.

The alternative RES specification featured increased levels of intermittency, due to the removal of hydro power from the list of viable sources of generation, thereby increasing the amount of intermittent renewable and back-up fossil fuel based generation significantly, along with the amount of on-site energy storage specified.

This resulted in a significant increase in the range of RES surplus/deficit values. Since the developed energy pricing strategies are based upon these values, the alternative RES specification also had a significant impact upon energy pricing. The pricing strategies use of RES surplus/deficit ranges to define energy price points meant that the ability for energy prices to reflect subtle variations in RES was markedly reduced under the alternative specification. This is a function of the design of the pricing strategies themselves, and is intended to limit exposure to financial risk and large and unpredictable price fluctuations.

One potential solution to this issue would be to fix the RES surplus/deficit range attributed to each pricing point, with a larger range of values resulting in a larger range of pricing points (possible under the RTP strategy). While this would result in even greater levels of DR, such an approach would increase the extent of the financial risk to which residential consumers are exposed, thereby decreasing the likely overall viability of variable energy pricing. Striking the appropriate balance between these two conflicting objectives is of great importance in the real-world deployment of variable energy pricing. An alternative solution is investigated in the following section, which examines the impact of increasing the difference in price between each pricing increment.

The decreased sensitivity of energy pricing to fluctuations in the RES/demand balance was found to lead to fewer changes in energy prices throughout the day. This limits the number of opportunities households have to make financial savings by engaging in DR. Naturally, the pricing strategies with the least amount of pricing increments (VToU and VCPP) are the most susceptible to this effect, with mean RES conditions seeing no variation in pricing occurring in any of the simulated scenarios under VCPP.

At the individual household level, the results indicate that the level of DR achieved is not intrinsically linked to the price of energy. In some instances, average household bills were found to decrease despite an increase in average household energy consumption. This appears to suggest that engaging in DR does not always yield direct and proportionate rewards for consumers - a result which is unlikely to aid the perceived viability of variable pricing (as deployed in this study) among consumers.

The household level analysis conducted also highlighted the likelihood for single DR actions to cause a greater impact upon the overall demand (and therefore DR) of small households i.e. those with fewer permanent residents. Larger households can therefore be seen as being less susceptible to bill fluctuations, and were found to enjoy the greatest financial savings.

8.3 Consumer Price Elasticity of Demand

As discussed in Chapter 4, the consumer price elasticity of demand (CPED) plays a key role in determining the extent to which each household engages in DR in response to changes in energy pricing. This is especially true in this model, which uses CPED as a proxy for consumer response. As a result, the model can therefore be assumed to be highly sensitive to changes in CPED values.

However, given the importance of CPED values in both real-world applications and the application of the developed model, it is prudent to conduct a sensitivity analysis in order to gauge the extent of the impact upon model results that may be caused by changes in CPED values. Not only does such an analysis provide insight into how widespread changes to CPED impact the results of the SAHES model, but it is also useful in accounting for the potential for inaccuracy in the values used in the original model. Also of interest is the extent of the variation in the sensitivity of the model to CPED under various scenarios.

8.3.1 Scenario development

In order to include an appropriate range of elasticity values, a differential sensitivity approach was adopted. This involved altering the values used in the original model incrementally and independently. A differential approach was selected due to its ease of implementation, and its ability to quantify the sensitivity of the model to key parameters on an individual - not combinatorial - basis. These variations encompass significant increases and decreases in consumer elasticity, and represent the maximum and minimum values that might reasonably be expected within such a system. The selection of these values was informed by literature, with (Lijesen 2007) and (Borenstein 2005) in particular offering useful insight into the difficulties of estimating/measuring consumer energy demand elasticity. The values used are expressed as multiples of the values used in the original modelling process, as shown in Table 8-10 to Table 8-12. The lowest elasticity multiplier of 0.1, for example, means that CPED values are reduced to 10% of those used in the original model. This is applied uniformly across all forms of DR i.e. load shifting, curtailment and growth.

Table 8-10 - Table showing the various CPED values for consumers in the "low" elasticity bracket.

CPED Multiplier (re: Base Case)	Load Shifting			Load Curtailment/Growth		
	Non-elec. heating	Electric Heating				
		Low	High	Low	Med	High
0.1	0.015	0.015	0.113	±0.008	±0.015	±0.030
0.55	0.825	0.825	0.619	±0.041	±0.083	±0.165
1 (original)	*0.15*	*0.150*	*1.125*	*±0.075*	*±0.150*	*±0.300*
1.45	0.2175	0.218	1.631	±0.109	±0.218	±0.435
1.9	0.285	0.285	2.138	±0.143	±0.285	±0.570
2.35	0.3525	0.353	4.406	±0.176	±0.353	±0.705

Table 8-11 - Table showing the various CPED values for consumers in the "medium" elasticity bracket.

CPED Multiplier (re: Base Case)	Load Shifting			Load Curtailment/growth		
	Non-elec. heating	Electric Heating				
		Low	High	Low	Med	High
0.1	0.02	0.020	0.150	±0.010	±0.020	-±0.040
0.55	0.11	0.110	0.825	±0.055	±0.110	±0.220
1 (original)	*0.2*	*0.200*	*1.500*	*±0.100*	*±0.200*	*±0.400*
1.45	0.29	0.290	2.175	±0.145	±0.290	±0.580
1.9	0.38	0.380	2.850	±0.190	±0.380	±0.760
2.35	0.47	0.470	3.525	±0.235	±0.470	±0.940

Table 8-12 - Table showing the various CPED values for consumers in the "high" elasticity bracket.

CPED Multiplier (re: Base Case)	Load Shifting			Load Curtailment/Growth		
	Non-elec. heating	Electric Heating		Low	Med	High
		Low	High			
0.1	0.025	0.025	0.188	±0.013	±0.025	±0.050
0.55	0.1375	0.138	1.031	±0.069	±0.138	±0.275
1 (original)	*0.25*	*0.250*	*1.875*	*±0.125*	*±0.250*	*±0.500*
1.45	0.3625	0.363	2.719	±0.181	±0.363	±0.725
1.9	0.475	0.475	3.563	±0.238	±0.475	±0.950
2.35	0.5875	0.588	4.406	±0.294	±0.588	±1.175

As well as spanning the range of likely values that could reasonably be expected within any real-world application, these values are also intended to account for the likely use of automation technology and the resultant impact on elasticity which could arise from its use, namely its ability to facilitate significant increases in absolute CPED values with minimal disruption to consumers.

8.3.2 Community level results

The alternative CPED scenarios were tested under both minimum and maximum RES conditions during all four seasonal days. However, in order to simplify the discussion only results from summer and winter seasonal days are included, with the focus placed on the impact of CPED variation on the demand-supply matching ability of the model i.e. $r_{d:RES}$ and community DR engagement levels. Therefore, the impact on peak demand reduction is not included as part of this analysis. Results graphs for all pricing strategies and scenarios can be found in Appendix B.

The VToU results show a rising trend, with $r_{d:RES}$ levels increasing as CPED increases. This is illustrated in Figure 8-19 and Figure 8-20, which show the levels of $r_{d:RES}$ achieved by VToU under each CPED level for both minimum and maximum RES conditions in Summer and Winter respectively.

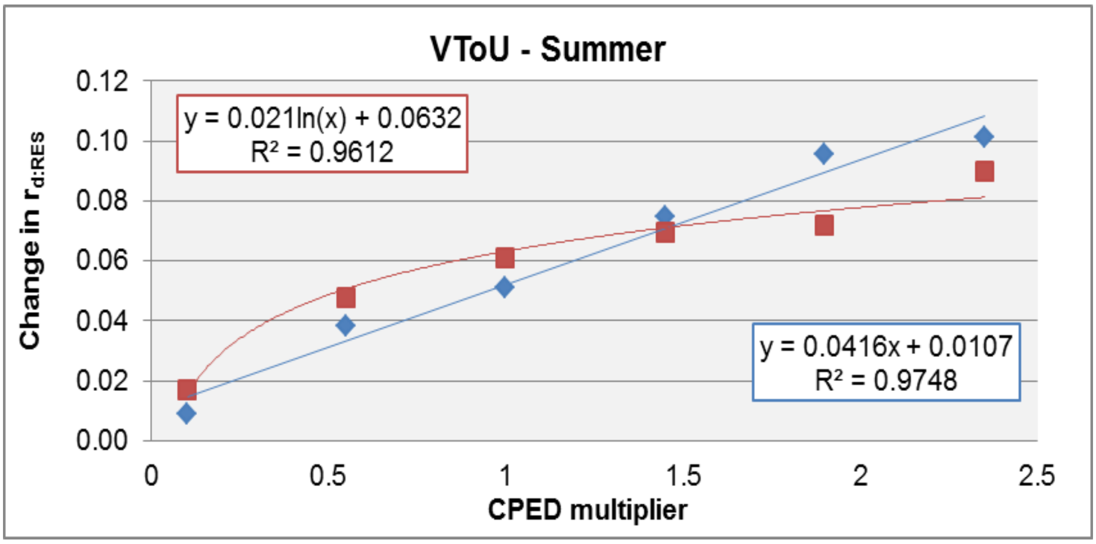


Figure 8-19 - Linear regression showing $r_{d:RES}$ achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

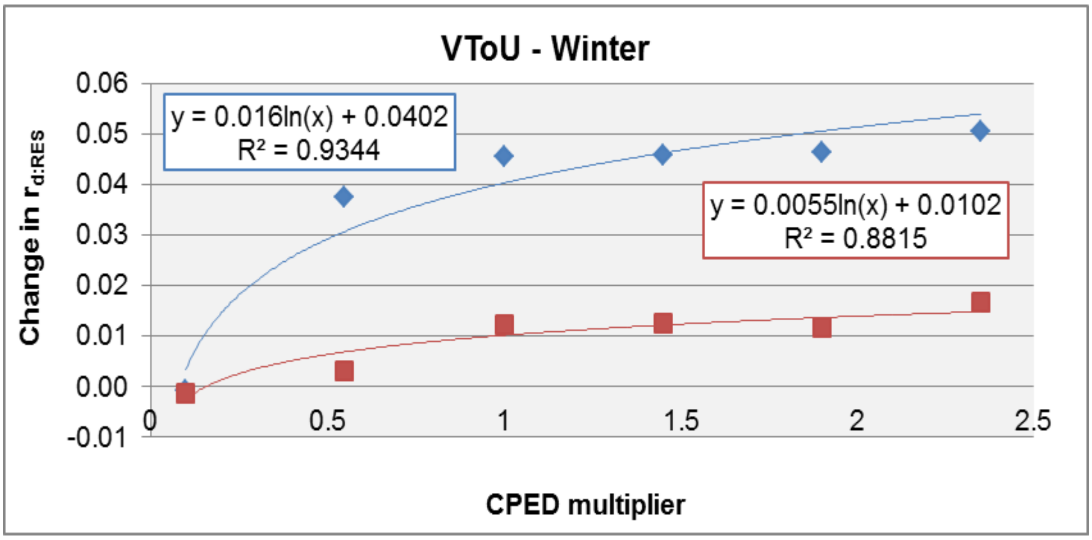


Figure 8-20 - Linear regression showing $r_{d:RES}$ achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

These results show that the change in $r_{d:RES}$ achieved by VToU is sensitive to changes in CPED, with a clear drop off point identifiable (in this case when the elasticity multiplier is around 0.5) beyond which very little change is achieved. This is indicative of a level of CPED below which very little DR can likely be achieved. Summer results also exhibit a greater magnitude of $r_{d:RES}$ variation than winter, which indicates that the sensitivity varies seasonally. R^2 values of between 0.88 and 0.97 indicate that the curves shown represent the relationship between CPED and

$r_{d:RES}$ with a high degree of accuracy, meaning that changes in $r_{d:RES}$ can be closely linked to CPED values. This is a logical result which reflects the prominent role of CPED in the make-up of the model itself.

The results for RTP are shown in Figure 8-21 and Figure 8-22. High R^2 values (of between 0.90 and 0.98) again indicate a strong relationship between the two variables, even if the variation in $r_{d:RES}$ is not as pronounced as under VToU. Indeed, RTP has the highest mean R^2 value across all scenarios of all three of the pricing strategies. This result reinforces the fact that RTP is best equipped to translate the balance between energy demand and RES supply into pricing, by virtue of its increased number of pricing points. The winter results (shown in Figure 8-22) indicate a strong linear relationship between $r_{d:RES}$ and CPED values, with little difference in minimum and maximum RES conditions. In summer however, the difference is far more pronounced, indicating a significant seasonal variation in the relationship. Under maximum RES conditions, changes in $r_{d:RES}$ appear to plateau as CPED values increase, suggesting that increases in CPED values are failing to have an impact on $r_{d:RES}$. Only when the highest CPED value is reached is a further change in $r_{d:RES}$ triggered, suggesting that another DR action has become viable to consumers. However, under minimum RES conditions no such plateau is experienced, with changes in $r_{d:RES}$ increasing as CPED values increase. Together, these results show that while $r_{d:RES}$ values are closely linked to CPED, the sensitivity can vary according to both RES conditions and demand characteristics.

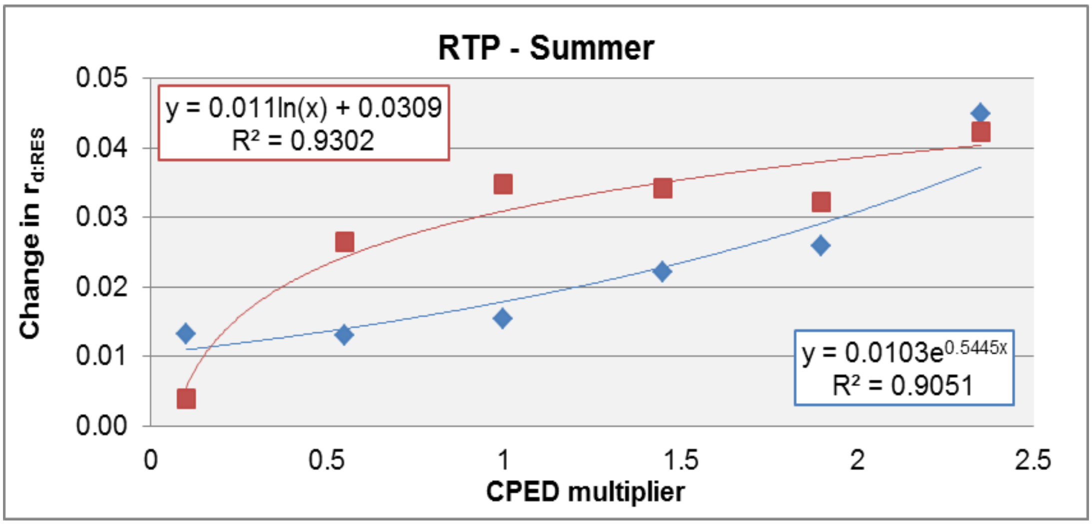


Figure 8-21 - Linear regression showing $r_{d:RES}$ achieved by RTP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

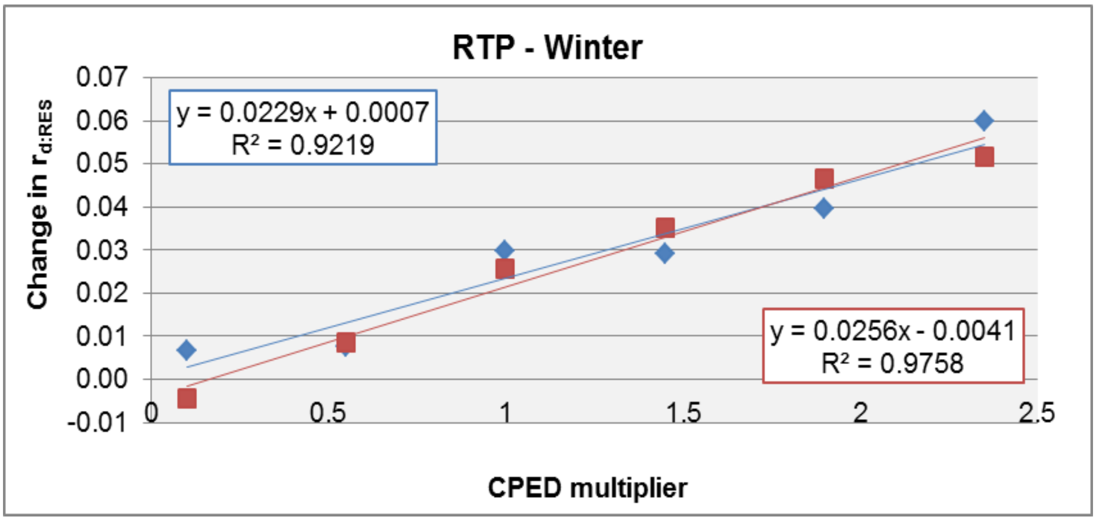


Figure 8-22 - Linear regression showing $r_{d:RES}$ achieved by RTP under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

VCPP results also indicate a linear relationship between CPED and $r_{d:RES}$, as shown by Figure 8-23 and Figure 8-24. The lack of price variation resulting from maximum RES conditions in the winter seasonal day means that no changes in $r_{d:RES}$ occurred under any of the CPED scenarios, as is visible in Figure 8-24. R^2 values are generally lower than those of VToU and RTP, which indicates that the relationship is more sensitive to other factors.

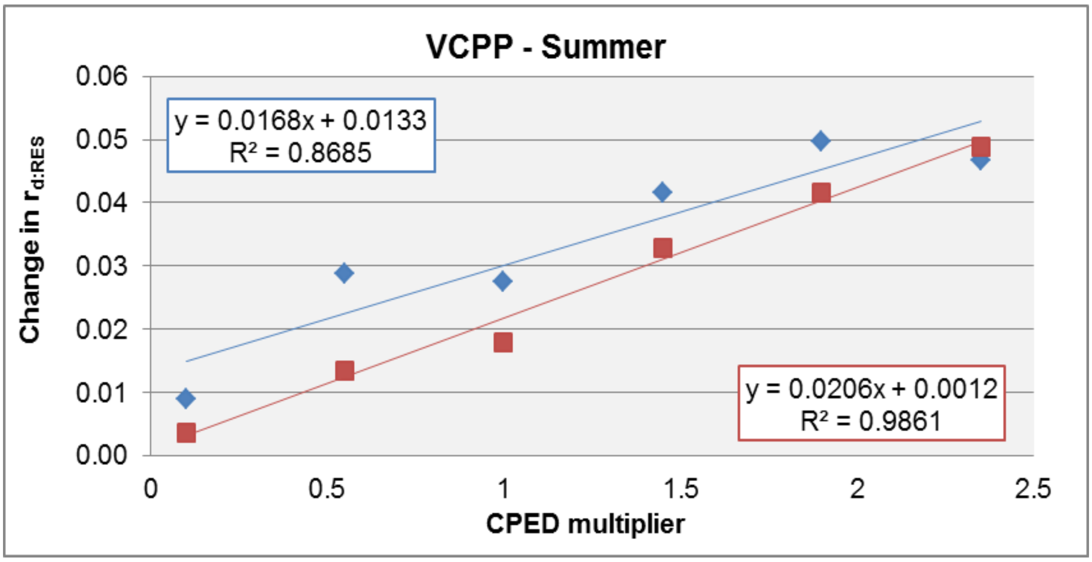


Figure 8-23 - Linear regression showing $r_{d:RES}$ achieved by VCPP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

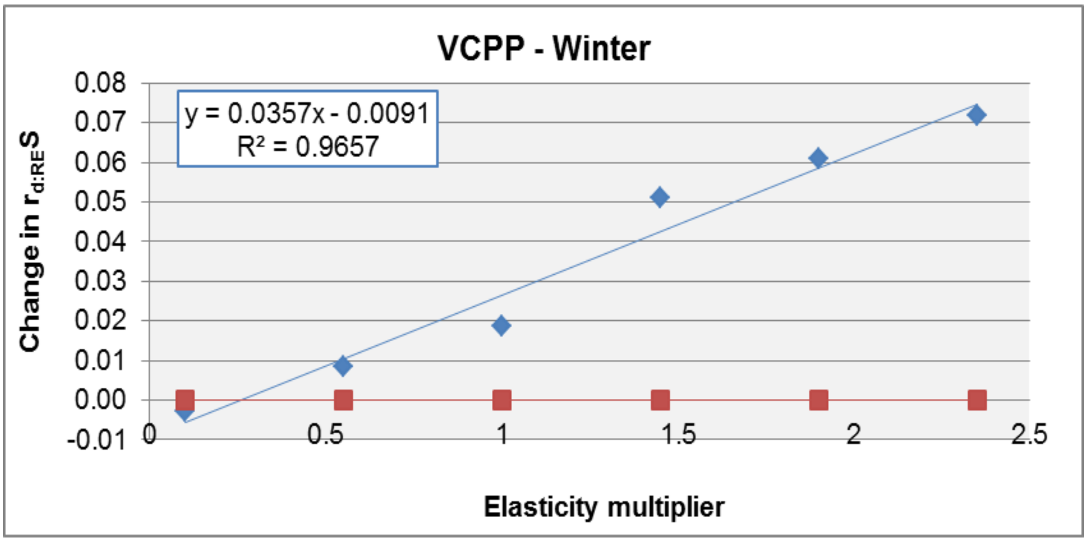


Figure 8-24 - Linear regression showing $r_{d:RES}$ achieved by VCPP under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

Community DR engagement levels i.e. the percentage of households which engage in some form of DR, were also found to be highly sensitive to CPED values, with the range in DR engagement rates between the maximum and minimum CPED values reaching a maximum of 45% (from 10% to 55%) for RTP under maximum RES conditions in Winter.

Unlike the relationship between CPED and $r_{d:RES}$ discussed above, the relationship between CPED and community DR engagement rates is found to be logarithmic in all of the examined scenarios, with a drop off in DR engagement occurring when CPED values reach a lower level, and a plateauing towards the higher CPED values. This is illustrated by Figure 8-25 to Figure 8-30, which show the summer and winter results for VToU, RTP and VCPP respectively.

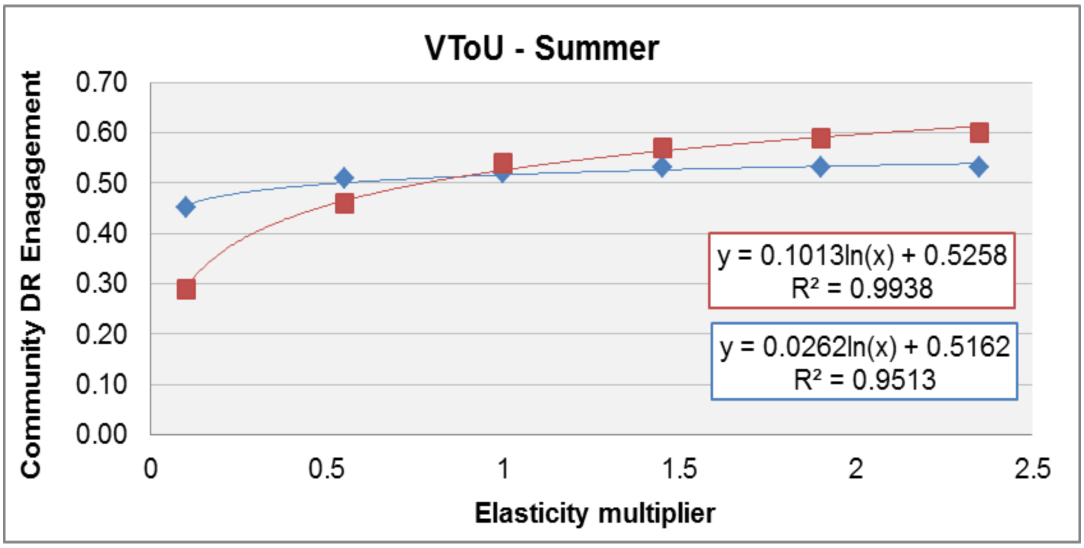


Figure 8-25 - Linear regression showing levels of DR engagement achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

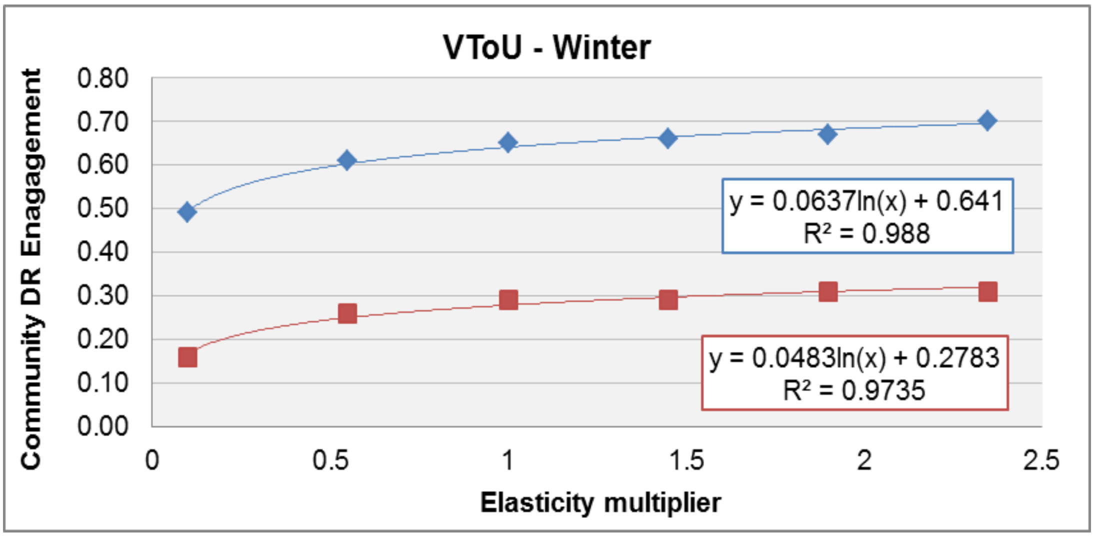


Figure 8-26 - Linear regression showing levels of DR engagement achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

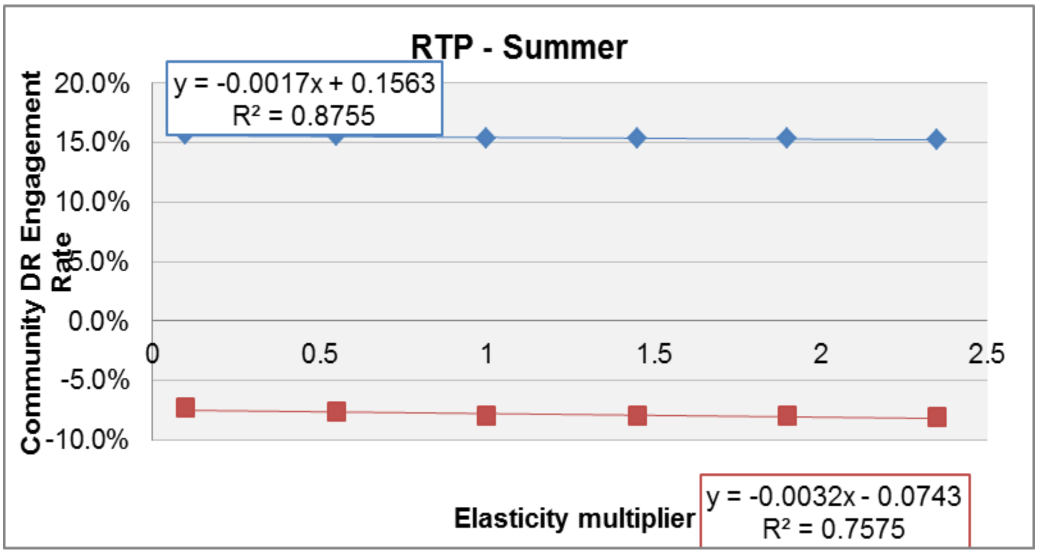


Figure 8-27 - Linear regression showing levels of DR engagement achieved by RTP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

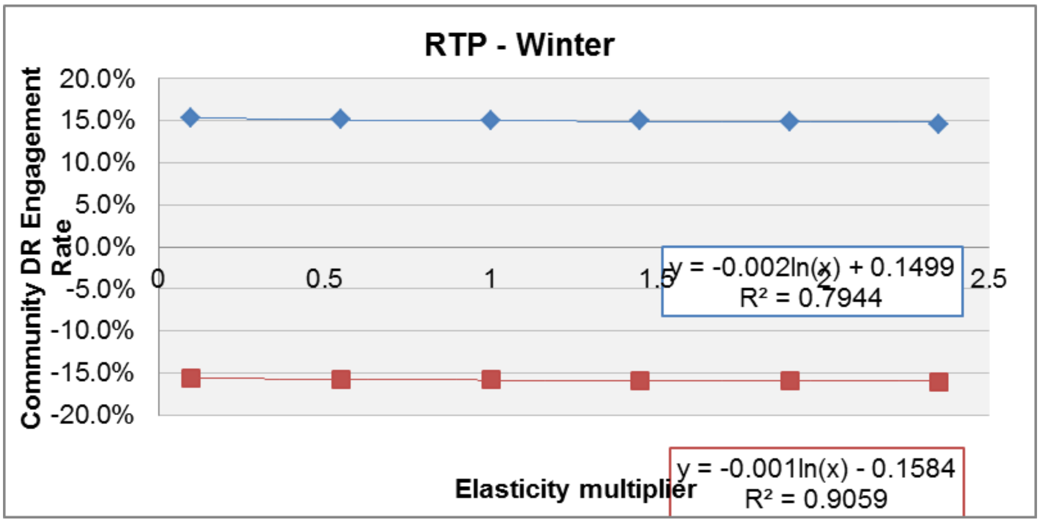


Figure 8-28 - Linear regression showing levels of DR engagement achieved by RTP under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

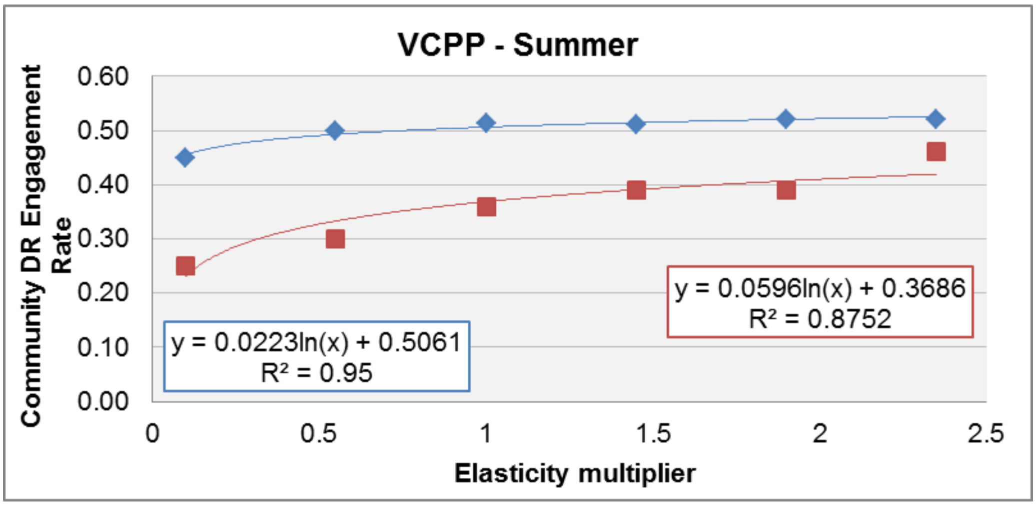


Figure 8-29 - Linear regression showing levels of DR engagement achieved by VCPP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

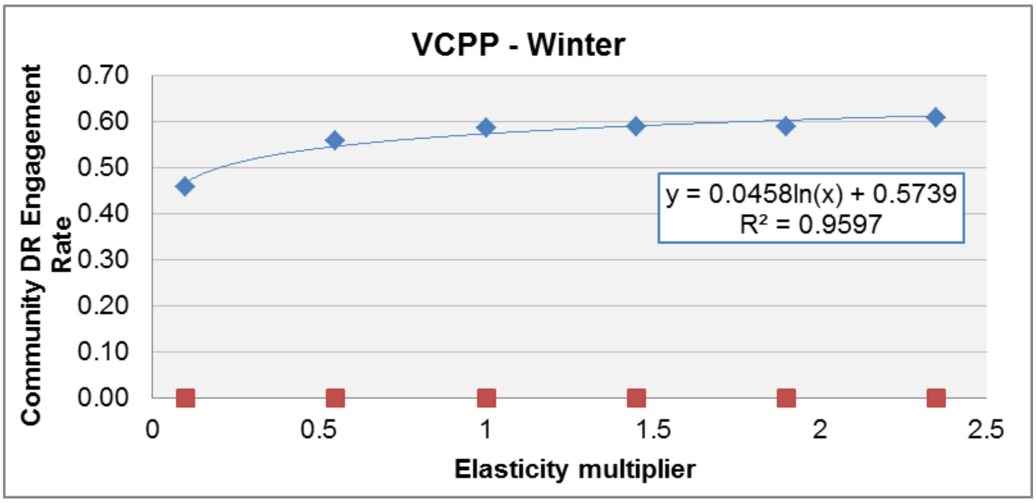


Figure 8-30 - Linear regression showing levels of DR engagement achieved by VCPP under minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

Peak DR engagement rates occur under VToU during minimum RES conditions in winter, with an engagement rate of 70%, with VCPP again failing to achieve any DR during maximum RES conditions. However, the results also suggest that there is a range of CPED values within which community engagement levels are most sensitive, bounded by the sharp drop off which exists at the lower end of the CPED range and the plateau which emerges towards the higher end of the scale. This suggests that beyond a certain point, further effort to increase CPED values may not be seen as time or cost effective, due to the limited returns that result.

8.3.3 Household level results

The focus of the analysis at the household level was the impact of CPED variation on household r_d values (the extent of DR) and the resulting impact on household energy bills.

In summer, the VToU pricing strategy was found to be most sensitive, with mean household r_d values ranging from 0.98 under the lowest CPED values to 0.88 under the highest, during maximum RES conditions (a change in mean household r_d of 0.104). This represents a significant increase in the responsiveness of the average household, and is illustrated in Figure 8-31. Similar results were observed across all three pricing strategies, with the corresponding graphs available in Appendix B.

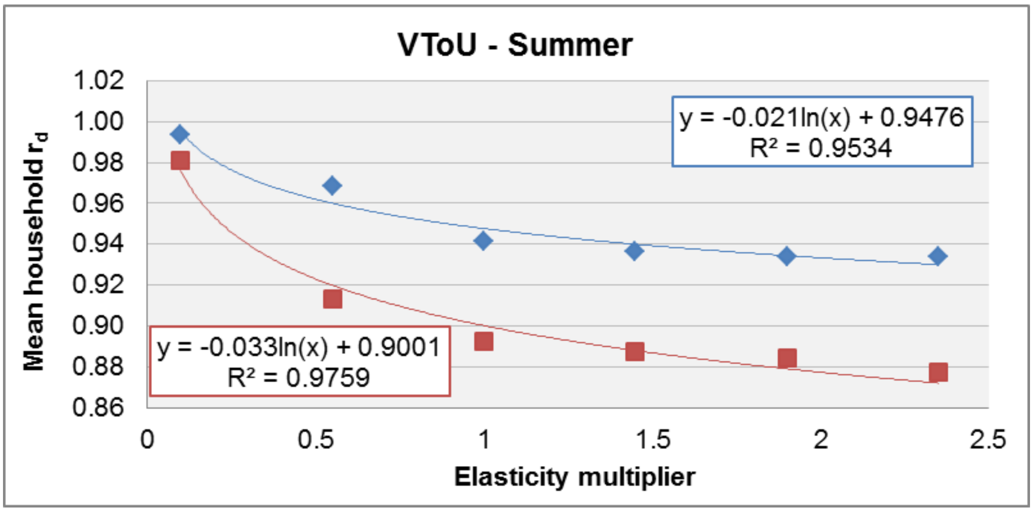


Figure 8-31 - Linear regression showing levels of mean household r_d values achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

Once again, these results indicate a logarithmic relationship between the two variables, which is reflected by a sharp drop off in DR under the lowest CPED scenario and a plateauing of DR under the highest. High R^2 values also illustrate the strength of the relationship between mean household r_d and CPED values.

But while these mean values provide a general indication of the level of DR resulting from each of the CPED scenarios, more detail is needed in order to understand the extent and variation in household r_d. This can be provided by considering all 100 household r_d values under the different CPED multipliers, as shown in Figure 8-32 and Figure 8-33, which show the r_d values under both minimum and maximum CPED scenarios for VToU in summer respectively.

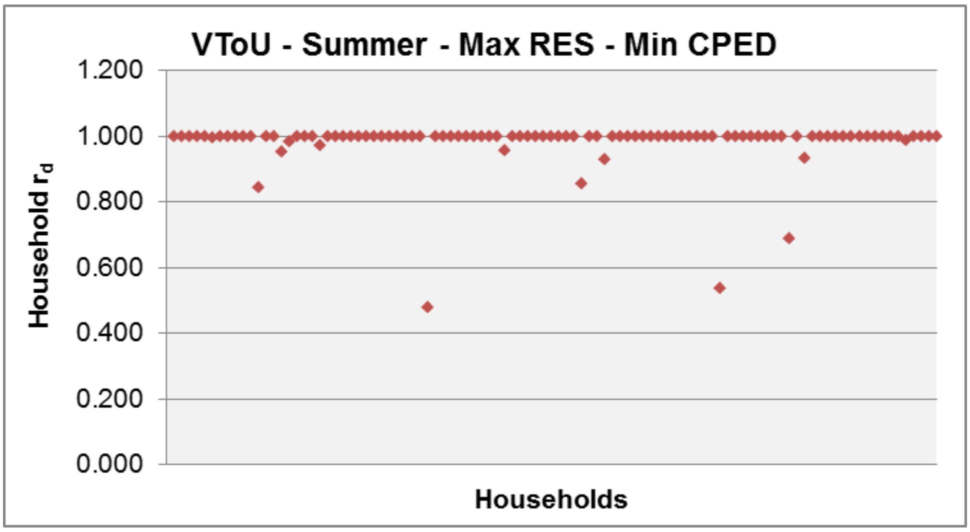


Figure 8-32 - Scatter plot showing the r_d values of all households which occur under the minimum CPED multiplier, under VToU during maximum RES conditions during the summer seasonal day.

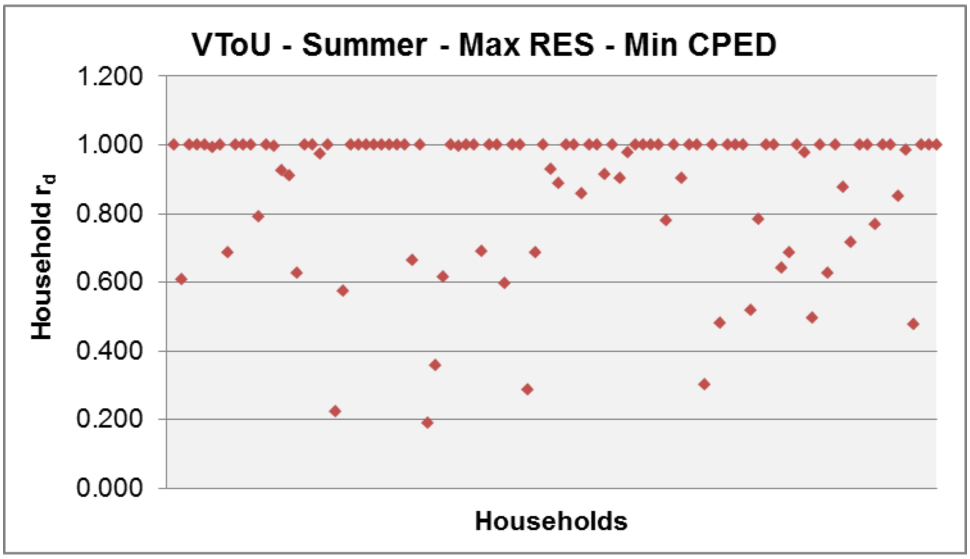


Figure 8-33 - Scatter plot showing the r_d values of all households which occur under the maximum CPED multiplier, under VToU during maximum RES conditions during the summer seasonal day.

These graphs show the extent of the difference in the levels of household r_d which result from changes to CPED, and show household DR levels to be highly sensitive to CPED. In changing the CPED from minimum to maximum in this scenario (maximum RES conditions in Summer under VToU) the number of non-responsive households decreases from 71 to just 40, with the number of household r_d values of less than 0.8 increasing from 3 to 26. This pattern is repeated during minimum RES conditions (where the range in mean household r_d is less - 0.060 compared to 0.104, as shown in Figure 8-31). This is illustrated in Figure 8-34 and Figure 8-35, and suggests that the impact of CPED on household responsiveness is insensitive to seasonal variation and changes in RES. This is confirmed in Table 8-13.

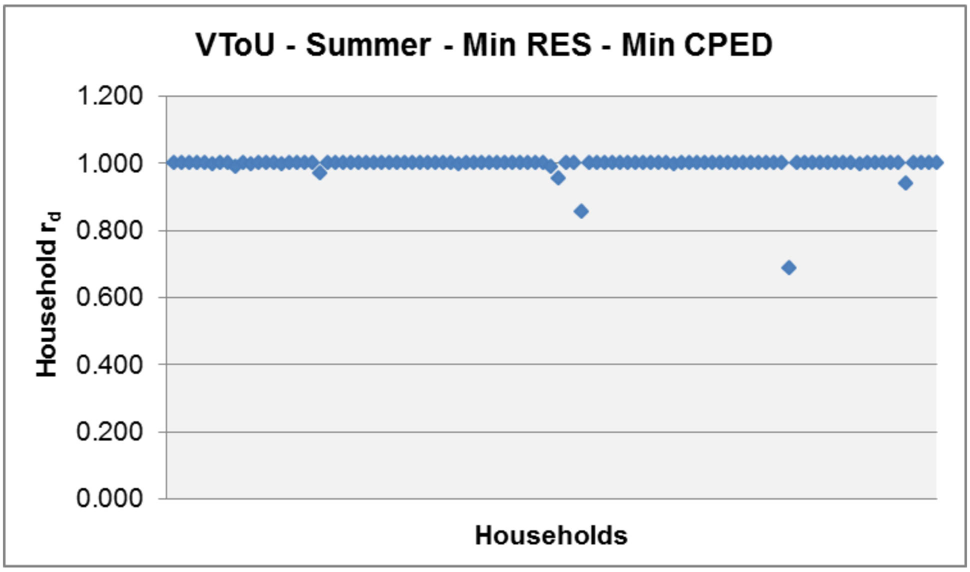


Figure 8-34 - Scatter plot showing the r_d values of all households which occur under the minimum CPED scenario, under VToU during minimum RES conditions during the summer seasonal day.

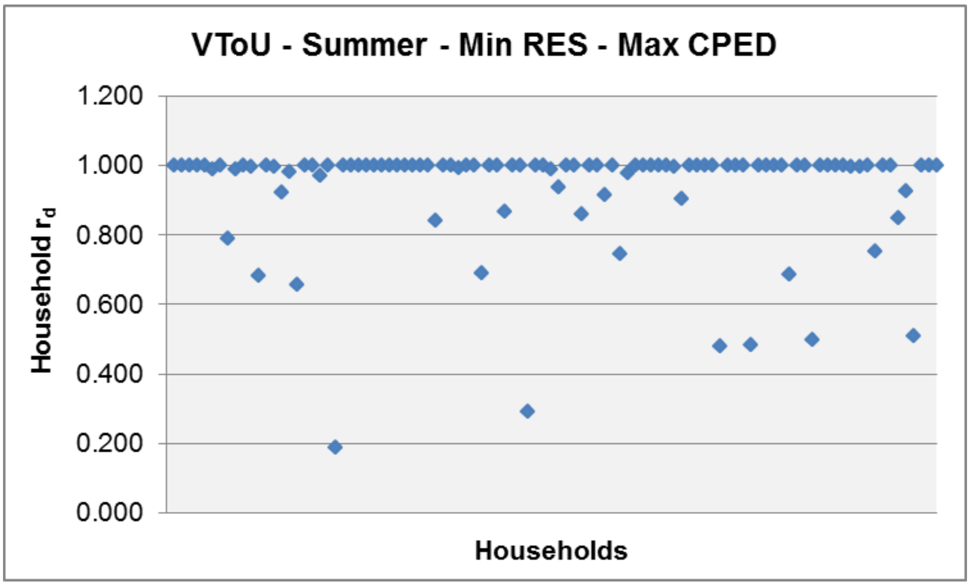


Figure 8-35 - Scatter plot showing the r_d values of all households which occur under the maximum CPED multiplier, under VToU during minimum RES conditions during the summer seasonal day.

Table 8-13 - Comparison of impact of CPED variation on household responsiveness under all summer and winter scenarios.

			Decrease in number of non-responsive households (min CPED - max CPED)	Increase in number of households with r_d <0.8 (max CPED - min CPED)
VToU	winter	min RES	21	14
		max RES	15	5
	summer	min RES	8	12
		max RES	31	23
RTP	winter	min RES	15	17
		max RES	45	20
	summer	min RES	7	8
		max RES	18	14
VCPP	winter	min RES	15	14
		max RES	0	0
	summer	min RES	7	10
		max RES	21	16

When the results of all three pricing strategies are compared, RTP in winter can be seen to be the most sensitive, in that it has the greatest range in both the number of non-responsive households and the number of households with r_d values of less than 0.8. This is followed by VToU in summer, with VCPP being least sensitive to changes in CPED.

The sensitivity of household bills to variation in CPED values was first assessed by taking the mean household change in energy bill, relative to the flat-rate pricing base case scenario. The relationship between the two variables was found to be linear, with little variation across the CPED scenarios, as shown in Figure 8-36 to Figure 8-39, which show the results of all three pricing strategies in summer.

The negative gradients of the trendlines show that bills decrease as CPED values increase. However, the magnitude of this variation is comparatively small in comparison to the other indicators included in this analysis - typically no more than 1-2%. This can be considered a negative result, as it illustrates the ineffectiveness of increasing elasticity in an attempt to reduce bill increases. There is therefore little in the way of financial reward for consumers who increase the responsiveness of their energy consumption behaviour.

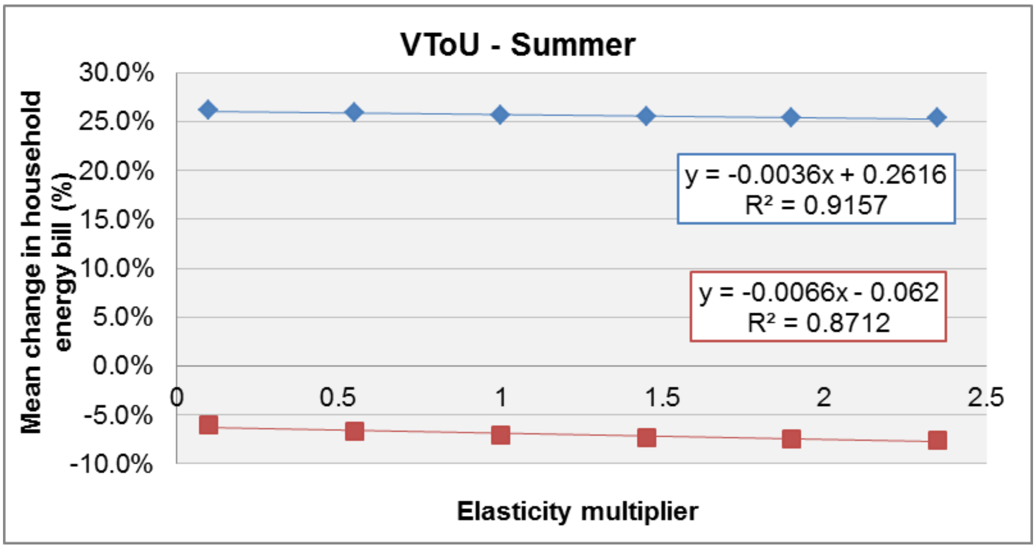


Figure 8-36 - Linear regression showing mean change in household energy bills achieved by VToU under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

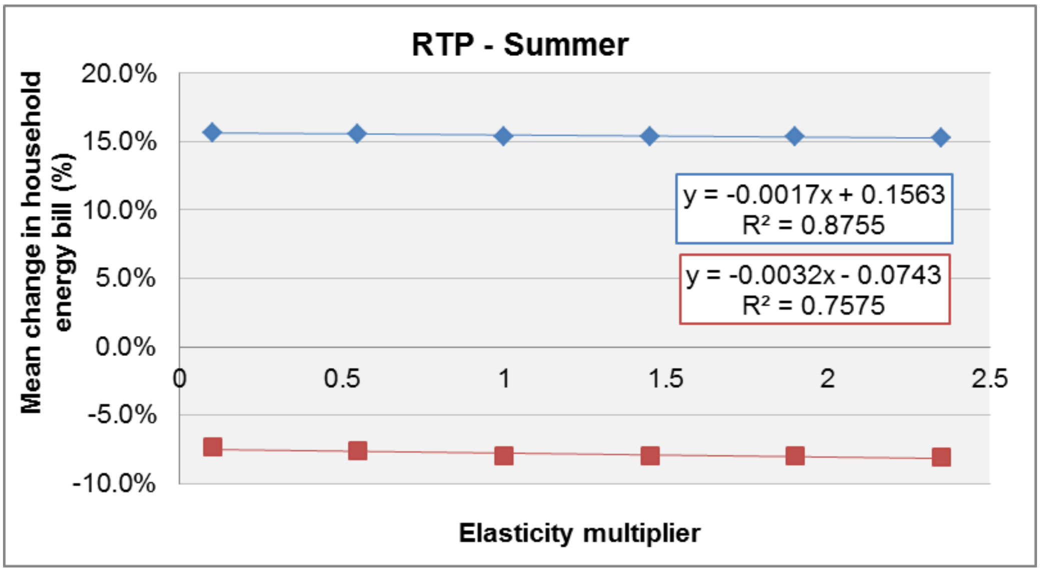


Figure 8-37 - Linear regression showing mean change in household energy bills achieved by RTP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

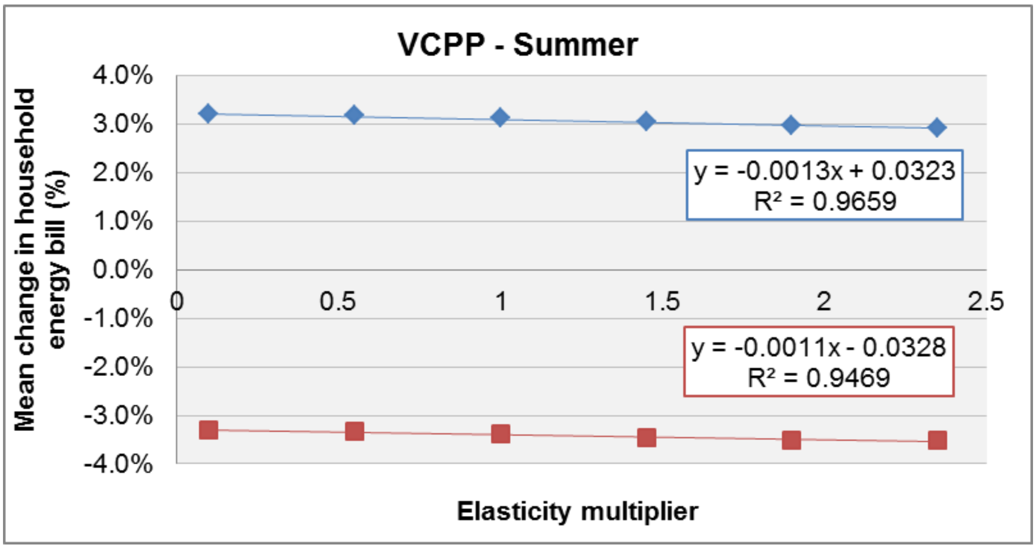


Figure 8-38 - Linear regression showing mean change in household energy bills achieved by VCPP under minimum (blue) and maximum (red) RES conditions, during the summer seasonal day.

8.3.4 Results discussion

This sensitivity analysis has examined the sensitivity of a range of community and household level DR indicators to changes in the consumer price elasticity of demand (CPED).

DR indicators such as $r_{d:RES}$ and the level of community DR engagement indicate that the relationship between DR and CPED is best described as a very weak logarithmic relationship i.e. curved, with sharp decreases in demand responsiveness towards the low CPED values and a plateau in the responsiveness achieved towards the higher end of the CPED scale. This suggests that there may be a point beyond which attempting to increase CPED levels could be seen to be cost-inefficient.

Interestingly, the results of this sensitivity analysis suggest that energy bills are not particularly sensitive to CPED, whereas community-level indicators such as $r_{d:RES}$ and community-wide r_d are. This is a significant finding, in that is suggests that households which increase their responsiveness are unlikely to see their bills reduce as a reward for doing so (under the three featured energy pricing strategies at least). With increases in CPED values failing to result in significant changes in energy bills, the incentive for consumers to adopt a more responsive approach towards consumption seems unlikely to be financial, and more likely to be more altruistic in nature. This is true of all three of the pricing strategies presented, and suggests that additional financial incentives may also be required e.g. one that increases more directly in line with consumer responsiveness. This result is significant, in that it shows the context of SAHES to be subject to the same potential drawbacks of variable pricing as other, more conventional areas. As discussed in Chapter 4, this can be addressed using additional financial incentives which provide additional rewards for active consumers.

Increases in CPED values were, however, found to result in significant increases in community-level DR, with the demand-supply match ($r_{d:RES}$) and community-wide DR engagement rates (r_d) both proving to be highly sensitive to CPED. This result suggests that attempts to promote DR using appeals to community collaboration and like-mindedness may yield some success.

8.4 Price Ratio Variation

In addition to testing the impact upon the model caused by alterations to consumer consumption characteristics, it was also deemed necessary to examine the impact of altering the way in which the various pricing strategies were applied, and to the financial incentives/motivation they provided.

As discussed in previous chapters, the model's use of consumer price elasticity of demand (CPED) as a proxy for consumer response to variable pricing means that it relies upon temporal price variations as the main driver for DR. It therefore stands to reason that varying the ratio between maximum and minimum energy costs (and by extension the level of financial incentive) is the simplest and most appropriate way of adding price variation to the model (in a way that allows for comparable results). Indeed, this area was also the subject of an investigation by Heberlein and Warriner, who found that higher price ratios lead to increased consumer awareness and therefore to increased levels of responsiveness (Heberlein & Warriner 1983).

8.4.1 Scenario development

As with the previous sensitivity analyses, a differential approach was adopted which involved incremental variations in the price ratio, relative to the reference value provided by the original model. The original model has a fixed price ratio of 3:1, meaning that the maximum price which occurs on any given day (and under any of the three variable pricing strategies) is three times higher than the minimum price. Since a ratio of 1:1 would be incapable of achieving any DR, a minimum ratio of 1.5:1 was deemed appropriate. Defining the maximum ratio involved consulting the literature as well as considering at what level a pricing ratio would cause a disproportionate and unnecessarily high negative impact on consumer bills. A ratio of 5:1 was identified as being the point beyond which maintaining such as balance would become impractical, and is also in-line with the maximum values found in the literature (summarised by Tracey and Wallach (Tracey & Wallach 2003)). Table

8-14 shows the breakdown of the six incremental price ratios implemented as part of the sensitivity analysis.

Table 8-14 - Price ratio sensitivity analysis scenarios.

Scenario	Price ratio (max:min)
A	0.75
B	1.5
C	2.25
Original	**3**
D	3.75
E	4.5
F	5.25

In order to maintain comparability, prices were once again set to ensure that the average price within any of the four seasonal days and under any of the pricing strategies included in the simulation stayed equal to the base case flat rate price (£0.2/kWh).

This method of introducing variation does not alter the shape of the pricing profile for any given timestep. However, as shown in Figure 8-39, it does vary the difference in price that occurs between the timesteps.

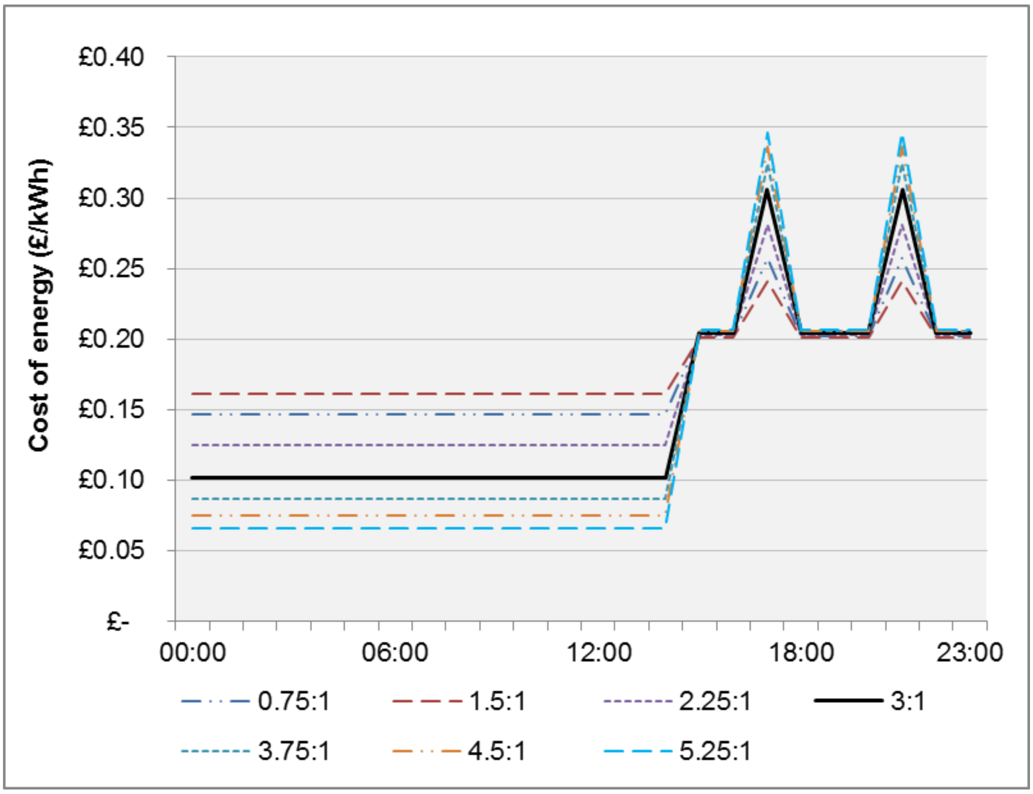


Figure 8-39 - Graph showing the impact of price ratio variation upon VToU pricing profile under maximum RES conditions during the spring seasonal day.

Since the magnitude of the price difference that exists between the various pricing levels is one of two primary drivers of DR in the model, these differences therefore have a significant impact on the levels of DR achieved.

8.4.2 Community level results

The alternative price ratio models were tested under both minimum and maximum RES conditions during all 4 seasonal days. As with the previous sensitivity analysis (section 8.3) the focus of the community level results analysis is the impact - in this case of price ratios - upon $r_{d:RES}$ and community DR engagement values. The results for all the modelled scenarios can be found in Appendix B.

Once again, the primary indicator of DR is $r_{d:RES}$. The results for all three pricing strategies and price ratio scenarios for the spring seasonal day are shown in Figure 8-40 to Figure 8-42.

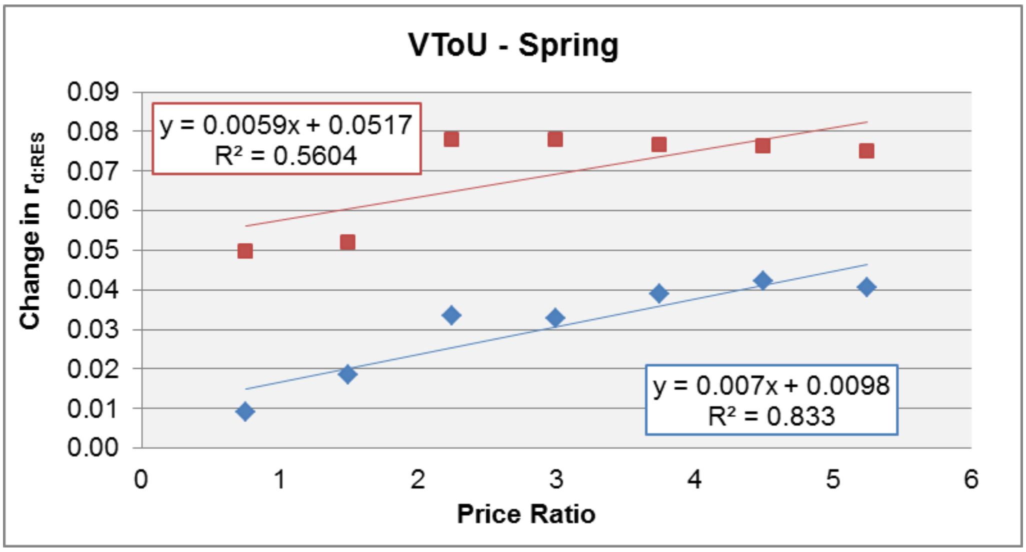


Figure 8-40 - Linear regression showing the relationship between $r_{d:RES}$ and price ratio, for the VToU pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

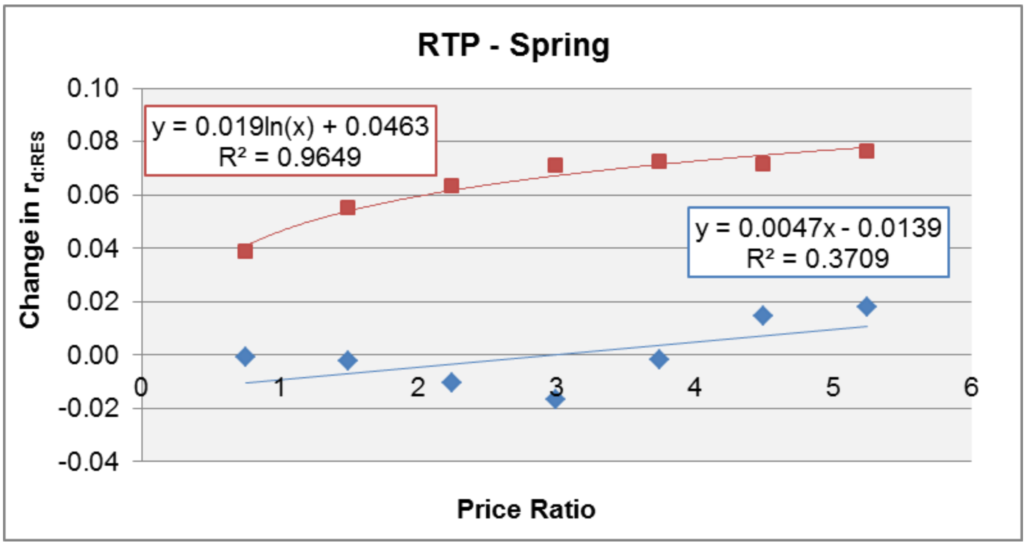


Figure 8-41 - Linear regression showing the relationship between $r_{d:RES}$ and price ratio, for the RTP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

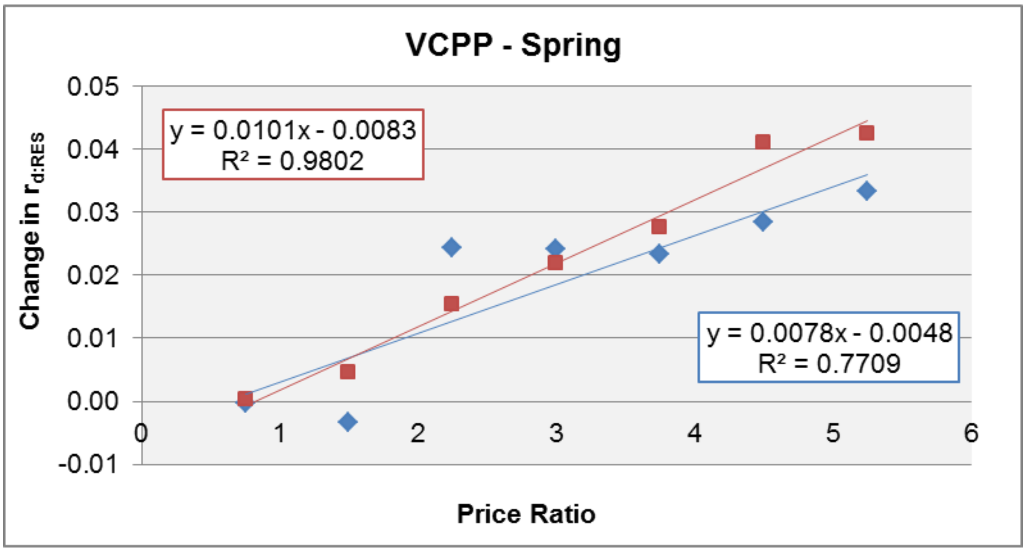


Figure 8-42 - Linear regression showing the relationship between $r_{d:RES}$ and price ratio, for the VCPP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

Under the VToU strategy, the lowest two price ratios (0.75:1 and 1.5:1) result in similar, modest $r_{d:RES}$ increases under both minimum and maximum RES conditions. From a price ratio of 2.25:1 and upwards however, a jump in $r_{d:RES}$ increases is evident. These two distinct groupings indicate a price ratio threshold above which significant additional DR is facilitated.

Under RTP this effect is not seen, but the range in $r_{d:RES}$ increases is similar to that of the VToU results (approximately 0.04 between the maximum and minimum $r_{d:RES}$ increases). One interesting result is the variation in $r_{d:RES}$ which occurs during minimum RES conditions. Variation such as this (which occurs at, or very close to zero) does not follow the logical trends exhibited in other results, and stems from the fact that at that level of detail, near-identical DR actions can cause different impacts on correlation coefficients. This effect can be seen elsewhere in the results, though to a lesser extent.

VCPP also has a similar range in $r_{d:RES}$ values, with maximum RES conditions resulting in the strongest relationship between price ratio and $r_{d:RES}$. Under minimum

RES conditions, the aforementioned threshold effect can again be seen, as shown in Figure 8-42.

As expected, these results show $r_{d:RES}$ values increasing as price ratios increase, indicating that as the level of financial incentive associated with DR increases, the level of DR also increases. However, the impact of these changes is limited, with a maximum range of $r_{d:RES}$ values of approximately 0.04 from minimum to maximum price ratios (occurring under VCPP, during maximum RES conditions). As discussed in the previous chapter, a change in $r_{d:RES}$ of this magnitude is better illustrated by considering the change in the daily demand profile associated with such a change in $r_{d:RES}$. Figure 8-43 shows the difference in community demand (relative to the original, base case demand) associated with a $r_{d:RES}$ increase of 0.04, which occurs under VCPP under maximum RES conditions during the spring seasonal day, with a price ratio of 5.25:1.

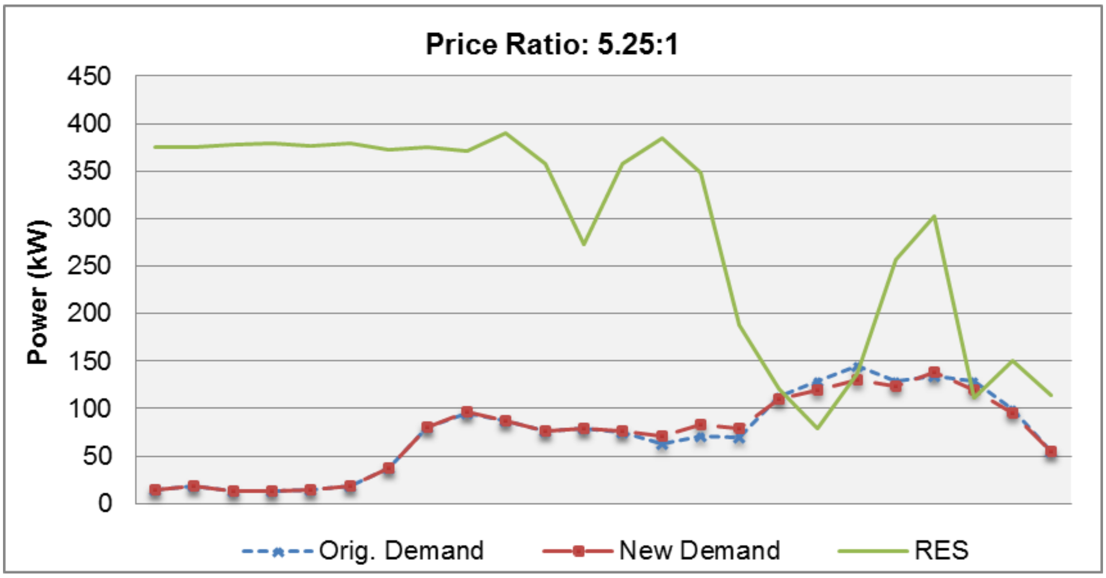


Figure 8-43 - Graph showing the difference in demand-supply match corresponding to an increase in $r_{d:RES}$ of 0.04.

The levels of community DR engagement which occur under the various price ratios show the extent to which the community-wide DR discussed above is shared amongst all 100 households. The results for all three pricing strategies are shown in

Figure 8-44 to Figure 8-46, which show the levels of community DR engagement across both minimum and maximum RES conditions during the spring seasonal day across all price ratio scenarios.

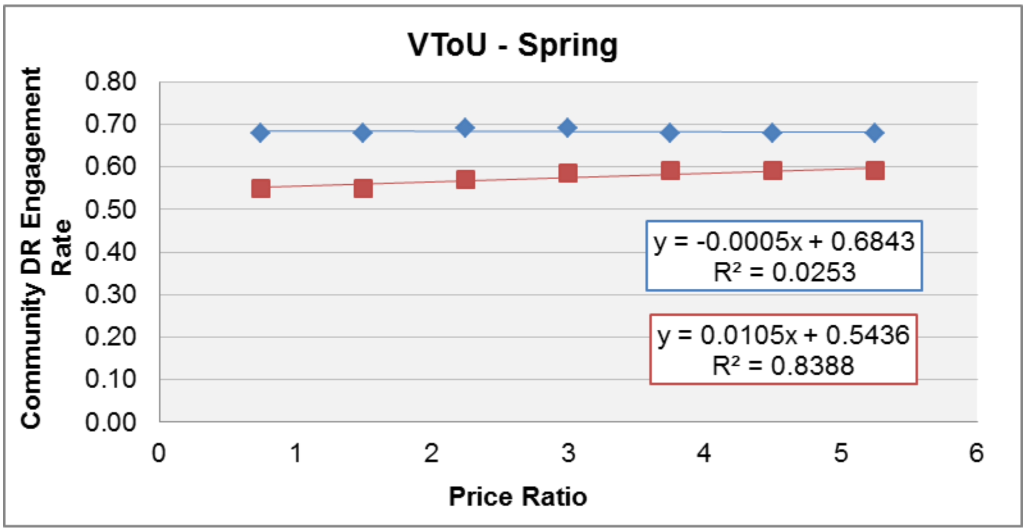


Figure 8-44 - Linear regression showing the relationship between community DR engagement rates and price ratio, for the VToU pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

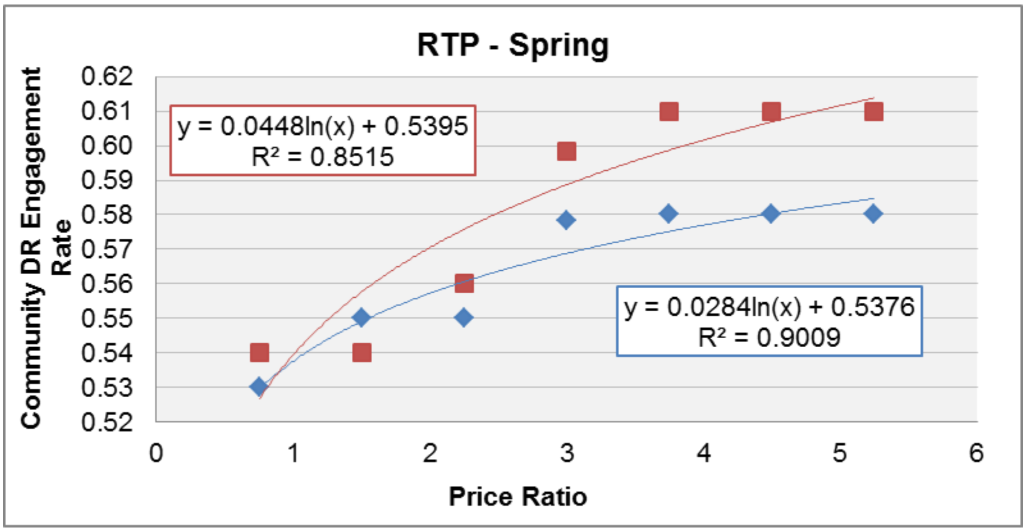


Figure 8-45 - Linear regression showing the relationship between community DR engagement rates and price ratio, for the RTP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

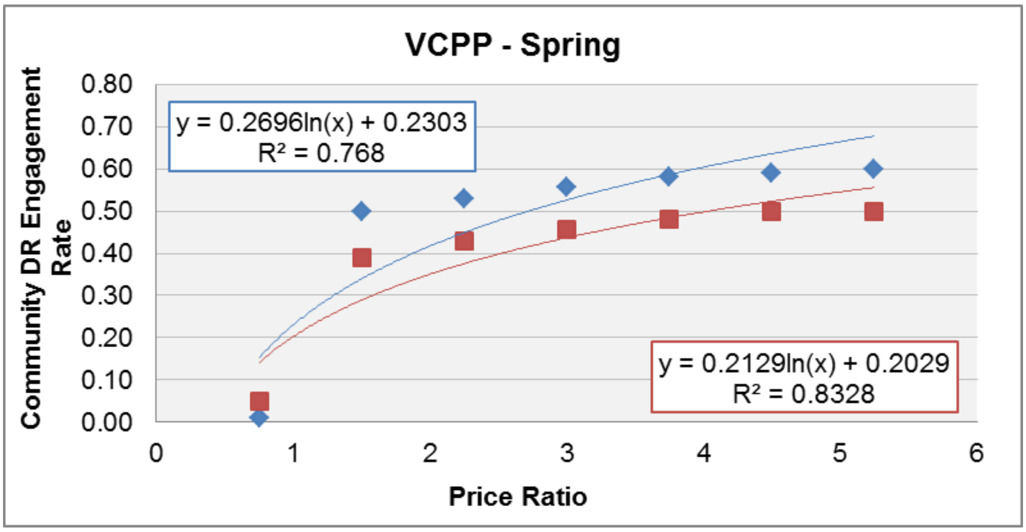


Figure 8-46 - Linear regression showing the relationship between community DR engagement rates and price ratio, for the VCPP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

Under VToU, the engagement rate varies by just 1% under minimum RES conditions, while maximum conditions see a range of 4%. Similarly, the RTP results show a range of 5% and 7% for minimum and maximum RES conditions respectively. RTP also suggests the existence of multiple thresholds, via the stepped increases in DR engagement rates which occur under both minimum and maximum RES conditions. These results show that while there appears to be a link between price ratio and DR engagement rates, the actual impact on the number of households engaging in DR is insignificant. In addition, the relatively low R^2 values suggest that price ratio is not a good predictor of DR engagement rates.

The same is not true of the VCPP pricing strategy however. As shown in Figure 8-46, DR engagement rates can be seen to increase gradually as the price ratio increases. The notable exception is provided by the steep drop-off in DR engagement at the lowest price ratio, with both minimum and maximum RES conditions resulting in engagement rates of less than 10%. This suggests that a price ratio threshold exists between 0.75 and 1.5, below which almost no DR is achieved.

8.4.3 Household level results

As with the previous sensitivity analysis, the focus of the household level analysis is the impact of price ratio variation on household r_d values, which expresses the extent of DR engaged in by an individual household, and the resulting impact on household energy bills. The mean household r_d values indicate that household DR is sensitive to variation in price ratio, as shown by Figure 8-47 to Figure 8-49.

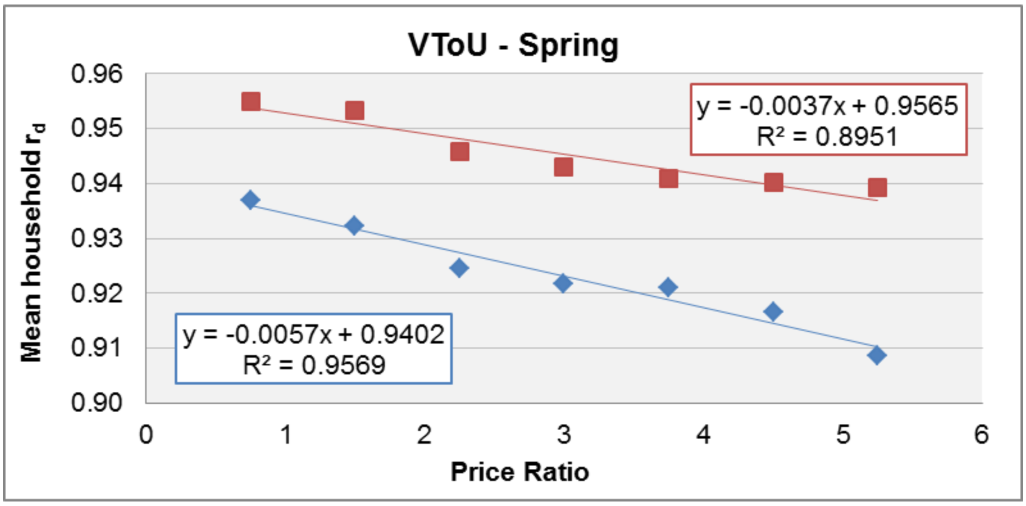


Figure 8-47 - Linear regression showing the relationship between mean household r_d and price ratio, for the VToU pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

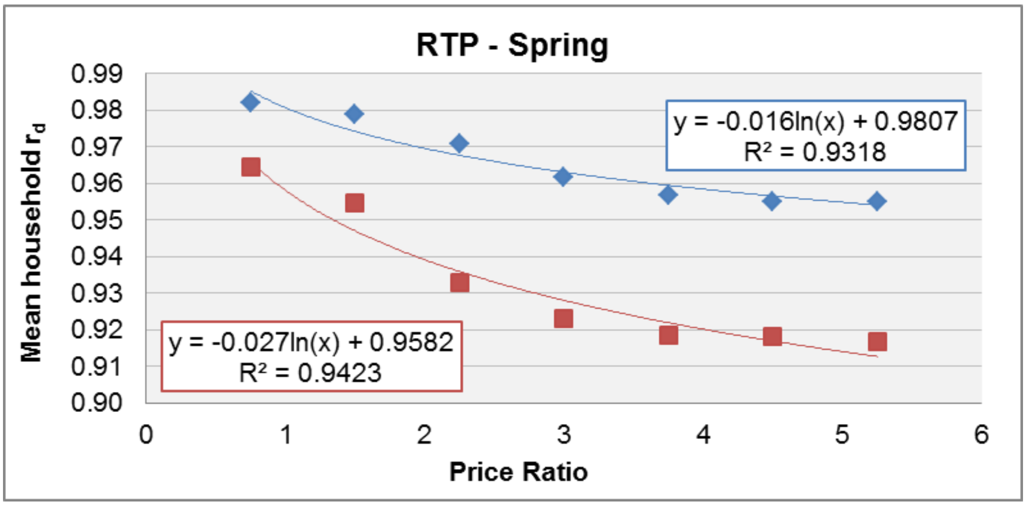


Figure 8-48 - Linear regression showing the relationship between mean household r_d and price ratio, for the RTP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

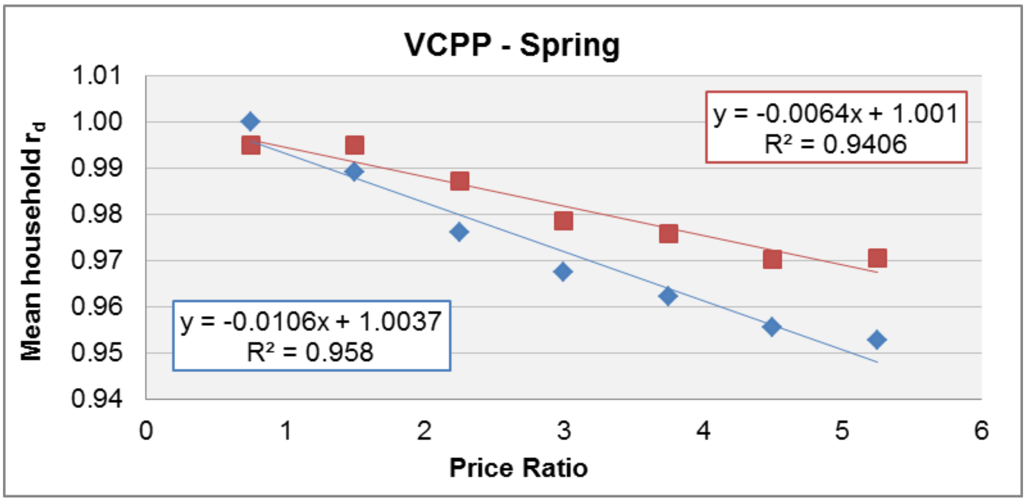


Figure 8-49 - Linear regression showing the relationship between mean household r_d and price ratio, for the VCPP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the spring seasonal day.

These results also show that higher price ratios result in greater levels of DR, this time exhibited by a reduction in mean household r_d values. However, as in section 8.3, a more meaningful comparison can be achieved by examining all 100 households. Figure 8-50 and Figure 8-51 show the r_d values for all 100 households which occur under minimum and maximum price ratio scenarios respectively, during maximum RES conditions on the spring seasonal day under the VCPP pricing strategy.

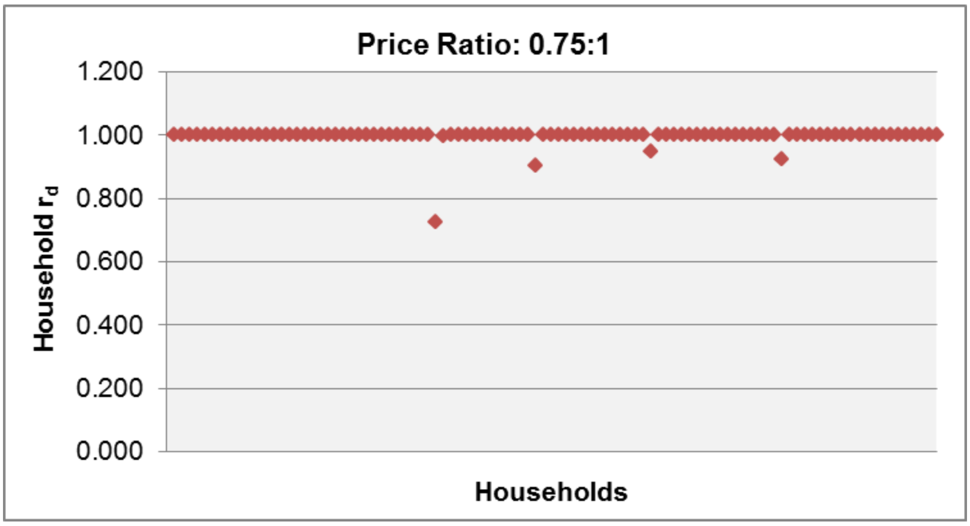


Figure 8-50 - Scatter plot showing the r_d values of all households under the minimum price ratio, under VCPP during maximum RES conditions in the spring seasonal day with a price ratio of 0.75:1.

Figure 8-51 - Scatter plot showing the r_d values of all households under the maximum price ratio, under VCPP during maximum RES conditions in the spring seasonal day with a price ratio of 5.25:1.

These figures show the dramatic increase in the number of households engaging in DR caused by the increase in price ratio. While just 4 households were found to engage in DR under the minimum price ratio, 50 did so under the maximum price ratio.

These figures also hint at the likelihood of household energy bills decreasing under the higher price ratios. Figure 8-52 to Figure 8-54 confirm this. These graphs show the relationship between price ratio and the change in the mean change in household energy bill (relative to the flat price base case) under all three pricing strategies during the spring seasonal day.

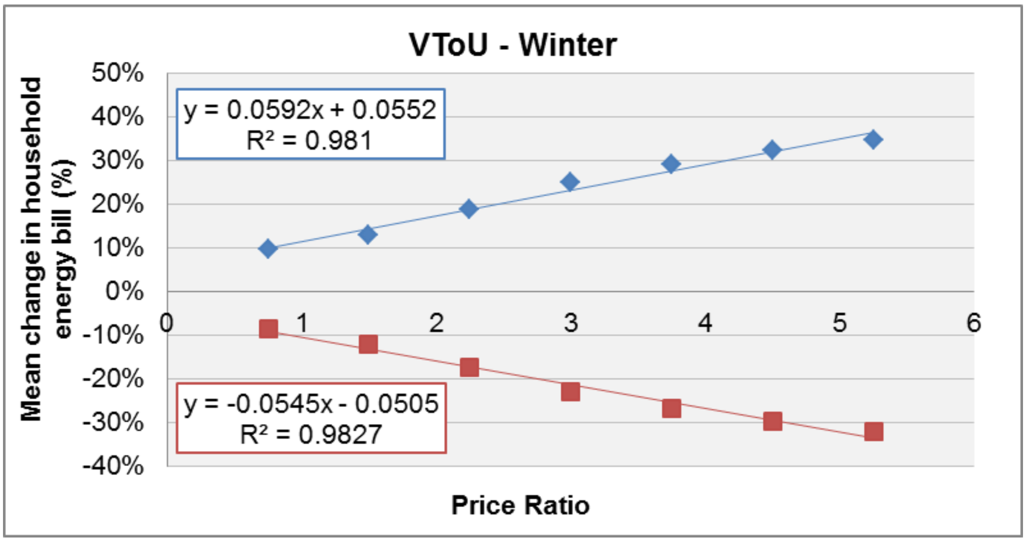


Figure 8-52 - Linear regression showing the relationship between household energy bills and price ratio, for the VToU pricing strategy during minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

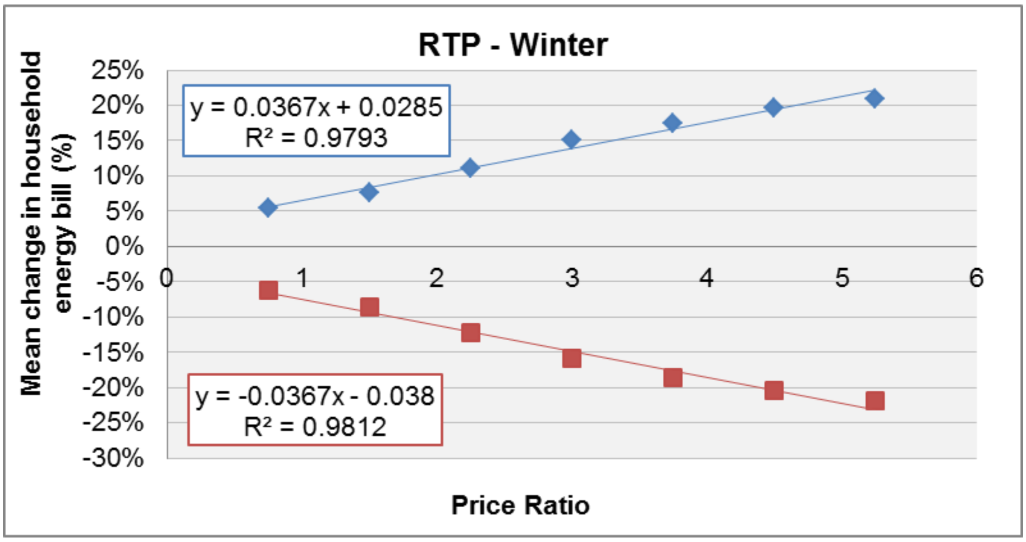


Figure 8-53 - Linear regression showing the relationship between household energy bills and price ratio, for the RTP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

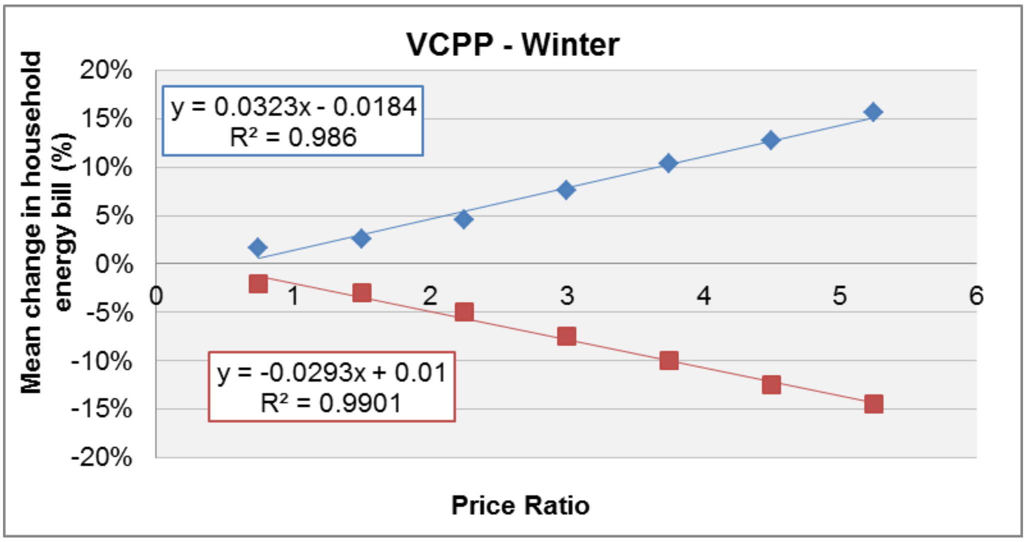


Figure 8-54 - Linear regression showing the relationship between household energy bills and price ratio, for the VCPP pricing strategy during minimum (blue) and maximum (red) RES conditions, during the winter seasonal day.

Once again, minimum RES conditions result in bill increases while maximum RES conditions result in decreases. The magnitude of these respective variations can clearly be seen to mirror one another, which shows the strength of the relationship between price ratio and household bills and the lack of any additional influence on the results. This is also reflected in the consistently high R^2 values returned, which show price ratio to be an effective predictor of mean household energy bill variation.

8.4.4 Results discussion

The results of this analysis show the levels of DR to be sensitive to price ratio variation. Since all DR decisions within the SAHES model are based on the resulting financial impact, this result comes as no surprise. However, it is the magnitude of the impact of price ratio variations which is of particular interest to this study.

At a community level, the results reflect the strength of the link between price ratio and the resulting levels of DR. Both $r_{d:RES}$ and DR engagement rate indicators show that the levels of DR achieved are affected by price ratio, but to a limited extent in most scenarios. Of the two indicators, DR engagement rate is more closely linked to price ratio.

It is at the household level however that the impact of price ratio variation is greatest, and likely to be most keenly felt. Household energy bills in particular have been shown to be highly sensitive to price ratio variation, with the difference between maximum and minimum price ratios corresponding to as much as a 25% change in mean household bills.

When viewed in comparison, it appears likely that consumers are more likely to notice the impact of price ratio variation than system operators, managers etc. While bill increases and decreases would effectively negate each other over time, there is likely to be a limit to the extent of bill fluctuations are deemed acceptable to consumers. This indicates the importance of finding an appropriate balance when it comes to defining the price ratios used in variable energy pricing. The emergence of a price ratio threshold i.e. a minimum price ratio, beyond which DR levels drop off dramatically, which was observed in the community level analysis, could potentially be used to inform this process.

8.5 Conclusions

This chapter has presented the design and results of three separate sensitivity analyses. In addition to aiding in the identification of key variables which play a role in facilitating DR, the sensitivity analyses presented also address the uncertainty associated with some of the values assigned to model variables in the original model. This creates a set of results which can be seen as being more resilient than those achieved through the original modelling process alone.

The results show that the SAHES model is sensitive to variation in a number of key parameters, namely the intermittency of RES, CPED and price ratio. Given the structure of both the SAHES model itself and the variable energy pricing strategies, a degree of sensitivity to these key variables was expected.

However, it is the extent of this sensitivity, and more specifically the variation in sensitivity which occurs across the simulated scenarios which is most informative. These variations provide some indication of the robustness of the SAHES model and the resilience of the three pricing strategies by demonstrating the existence of limits, outside which DR levels drop significantly. Findings such as these are likely to be highly influential in the development and deployment of variable energy pricing in real-world applications.

The results of the original model presented in Chapter 7 were found to be sensitive to changes in the intermittency of the RES specification, but to a limited extent. The results suggest that the pricing strategies developed are capable of operating effectively in a wide range of supply conditions. However, the greater RES deficit/surplus range which results from the increase in intermittent RES means that the pricing strategies with fewer pricing levels (VToU and VCPP) are less likely to result in price changes (the driver for DR in this study) as a result of the increase in the range of deficit/surplus values assigned to each pricing level. This lessens the effectiveness of these strategies at achieving DR. It should be noted that unlike the other sensitivity analyses conducted, the applicability of these results is limited by the fact that only one alternative has been tested.

Pricing ratios and CPED values were easily identifiable as key variables, given the way the model uses CPED as the basis for consumer DR. However, the sensitivity analyses provide a more in depth investigation into the extent to which changes in these values impact upon the levels of DR achieved by each of the pricing strategies. While the model can be seen as being sensitive to changes in both CPED values and pricing ratios, the results vary predictably and to a limited extent.

This suggests that the results of the model - and crucially the general conclusions that can be drawn from them - could reasonably be expected to be transferrable to other contexts and scales. As such, the SAHES model and the variable energy pricing strategies developed therein could be deemed as worthy of further investigation in other contexts and at different scales.

From a consumer perspective, the impact on household energy bills was once again deemed to be of great significance. Household energy bills have been shown to be relatively insensitive to changes in CPED - a surprising result which suggests that little financial motivation is provided to consumers to increase the elasticity of their demand. However, household bills have been shown to be highly sensitive to price ratio variation. As uniform increases or decreases in price ratio are likely to be cost neutral from the perspective of network operators, this variable is therefore considered to be much more important from a consumer perception standpoint.

8.6 References for Chapter 8

Borenstein, S., 2005. The long-run efficiency of real-time electricity pricing. *The Energy Journal*, pp.93–116. Available at: http://www.ucei.berkeley.edu/PDF/csemwp133R.pdf.

Heberlein, T.A. & Warriner, G.K., 1983. The influence of price and attitude on shifting residential electricity consumption from on- to off-peak periods. *Journal of Economic Psychology*, 4(1–2), pp.107–130. Available at: http://www.sciencedirect.com/science/article/pii/016748708390048X.

Lijesen, M.G., 2007. The real-time price elasticity of electricity. *Energy Economics*, 29(2), pp.249–258. Available at: http://www.sciencedirect.com/science/article/pii/S0140988306001010.

Tracey, B. & Wallach, J., 2003. *Peak-Shaving/Demand Response Analysis: Load-Shifting by Residential Customers*, Available at: http://sedc-coalition.eu/wp-content/uploads/2011/05/Tracey-Load-Shifting-by-Residential-Customers-2003.pdf.

Chapter 9: Conclusions

9.1 Thesis Review

As outlined in Chapter 1, the main research question addressed by this thesis is:

> *To what extent can variable energy pricing strategies be used to effectively promote domestic demand response in stand-alone hybrid energy systems?*

In order to meaningfully address this question, the following objectives were defined:

1. Establish the relevance of SAHES in the transition towards a more decentralised energy supply model, particularly within the remote and isolated communities in which they are found.
2. Establish the likelihood of the future widespread adoption of flexible energy consumption behaviour in SAHES
3. Review the existing literature regarding the design and implementation (both theoretical and practical) of variable domestic energy pricing
4. Generate a high resolution energy consumption model which is typical of a community that is served by a SAHES

5. Identify one or more variable energy pricing strategies which could be adapted to suit the context of SAHES by using the intermittent energy supply associated with hybrid renewable energy systems as the basis for energy price variation
6. Develop a model which replicates domestic demand response to varying energy prices
7. Develop a model which simulates the implementation of variable pricing strategies in SAHES, and the resulting demand response
8. Identify the key technical, social and economic factors affecting the viability of variable energy pricing in SAHES

The remainder of this section summarises the work presented for each of these objectives.

9.1.1 The relevance of SAHES

Chapter 2 examined the wider context within which the project sits - namely the concept of switching from the centralised energy supply model which is prevalent in the industrialised world towards a more autonomous model based on the use of Low and Zero Carbon Technologies.

Within this area, SAHES (and the remote and isolated communities in which they are most commonly deployed) were identified as being of particular relevance. This was due to the fact that such areas of society tend to be the worst served by the centralised energy model, with high energy costs and significant security and reliability of supply concerns providing the motivation for such communities to investigate alternatives. Furthermore, these communities are also seen to have the most to gain from switching to a more autonomous model, where hybrid systems based on small to medium scale Low and Zero Carbon Technologies are proving capable of providing an increasingly viable and cost-effective alternative.

Remote and isolated communities, and SAHES in particular, are therefore seen as an ideal and highly relevant context for further research, which can go on to better inform the transition towards a more decentralised energy model when this change is made by other sections of society.

However, a number of significant challenges were also identified, which to date have limited the extent to which SAHES have been deployed. Whilst this research has sought to partly address some of the technical challenges associated with their deployment - namely the reduction of the negative impact of RES intermittency through the introduction of domestic DR - there remain significant socio-economic barriers which must be addressed. Chief amongst these are financial barriers such as project finance availability and the capital costs associated with new and emerging technologies. The need for a receptive and supportive policy environment has also been identified as being crucial to securing the future widespread deployment of SAHES.

9.1.2 Domestic energy consumption and the potential for flexibility

Chapter 3 focussed on the subject of domestic energy consumption behaviour, and the evolution of the research and understanding into what influences it. A number of emerging trends were identified within the area of domestic consumption, with increasing appliance use and the general electrification of the home and its systems being the most notable.

Chapter 3 also examined the potential for domestic demand response. This was found to hinge on the receptiveness of consumers towards flexible/responsive consumption behaviour in general, but also on their willingness to adopt enabling technology to help facilitate it. As with other areas of research regarding domestic energy consumption, the need for consumer understanding and education was found to be paramount. The continued development of the understanding of what motivates domestic consumption and behavioural change was also found to be of particular importance, as was the response of consumers towards price variations over extreme short-term as well as medium to long-term timescales. It is the former where technology was found to play a particularly crucial role in facilitating domestic demand response. This rapidly emerging area of research looks set to play a decisive role in the design of energy pricing schemes, as the research community seeks to identify new and more successful ways to capitalise on rapid technological development.

While these findings are broadly applicable across the domestic sector, the desired outcomes associated with demand response schemes can be seen as being fundamentally different within SAHES than those within larger grid connected systems, with demand-supply matching taking precedence over the reduction of peak demand - a key distinction which is unique to SAHES.

9.1.3 The design and implementation of variable energy pricing

Having reviewed the key issues relating to domestic energy consumption and demand response, Chapter 4 went on to examine the concept of variable energy pricing in more detail. This involved an examination of a number of key concepts, including consumer price elasticity of demand, and the factors which affect consumers' willingness and ability to respond to price variations. A number of different forms of variable energy pricing were reviewed, and their strengths and weaknesses summarised.

A lack of research into the flexibility of demand in the extreme short-term i.e. over the course of a day or less, was identified. Once again, this served to further underline the importance of the role of enabling technology, and the need to further understand the receptiveness of consumers to its use.

Chapter 4 also examined the potential for the deployment of variable energy pricing in SAHES. It was concluded that their role as early adopters of renewable energy generation and their increased sense of connection with their energy supply would make SAHES an ideal context for the deployment of dynamic pricing.

Chapter 4 also identified the need for further research into the attitudes of domestic consumers towards demand flexibility, the use of financial incentives to promote demand response, and the use of enabling technology to facilitate greater levels of demand response. This was addressed through a consumer survey, which was presented in Chapter 5. This survey was designed to examine the issues outlined above, and to compare the attitudes of consumers in remote and isolated communities with those of consumers from more urban areas.

The findings of the survey suggest that not only are consumers are willing to engage in DR, but also that financial incentives are the most effective source of motivation for doing so. These results support the use of variable energy pricing to elicit demand response among domestic consumers. The results of the survey also showed that attitudes towards the adoption of demand response techniques did not vary significantly with location, with those in remote and isolated communities showing just as much willingness to adopt demand response as those in more urban areas. This result can be seen to broaden the applicability of the results. Lastly (and crucially), the survey results also indicated a high degree of receptiveness towards the use of cost-effective technology to help facilitate demand response in the home.

These results informed not only the design the of domestic energy consumption model developed in later chapters, but also the wider debate as to the willingness of consumers to engage with variable energy pricing, and their views on how such engagement could be facilitated. In the UK in particular, recent steps taken to ensure that domestic energy tariffs are simpler and fewer in number provide an interesting context to these results.

9.1.4 The modelling of domestic energy consumption in SAHES

Chapter 6 defined the aims and objectives of the modelling process, including the selection of an appropriate modelling methodology.

The first step in the modelling process involved the development of a conceptual model which is deemed to be representative of the type of community in which SAHES are typically introduced. A notional SAHES was developed, based on a combination of the detailed literature review and domestic consumer survey featured in previous chapters. The SAHES model featured a total of one hundred households ranging in size from two to five people. Households were allocated one of three pre-defined levels of demand elasticity and an appliance ownership/usage level. Based on the findings of the consumer survey presented in Chapter 5, a number of households were also specified as using electric space and water heating. Daily demand profiles were then generated using an existing high-resolution model, across four seasonally representative days. This resulted in a balanced, representative model of domestic energy consumption across the notional community.

9.1.5 Variable pricing strategy development

Chapter 6 described the development of a base case, which featured a total of three variable energy pricing strategies, adapted from some of the conventional forms of variable pricing summarised in Chapter 4. These were defined as Variable Time of Use (VToU), Variable Critical Peak Pricing (VCPP) and a form of hourly Real Time Pricing (RTP).

9.1.6 Demand response algorithm development

Chapter 6 also described the design, development and verification of the three forms of demand response featured in the model: load shifting, load curtailment and load growth. The algorithms used to incorporate these into the model were also described in detail. This approach implemented demand response on an hourly basis, thereby providing a sufficient resolution at which to examine the variation in energy supply and demand across a twenty four hour period. No assumptions were made as to how this response was enacted i.e. whether or not the response came as a result of enabling technology or direct consumer action, or both. Instead, the likelihood of different appliances being part of household demand response was encapsulated in the use of consumer price elasticity of demand values as the basis for demand response decisions within the model.

The result of the modelling process was a model which reflects the energy demand and supply conditions within a SAHES, and which serves as a basis through which to examine the impact of the deployment of the three variable energy pricing strategies.

9.1.7 The simulation process

Chapter 7 presented the results and introduced the performance metrics and indicators used to analyse them.

A total of thirty six simulations were conducted, accounting for minimum, mean and maximum renewable energy supply conditions across the four representative seasonal days and the three variable pricing strategies. Each simulation consisted of a set of energy demand and supply conditions, which resulted in the creation of an hourly energy pricing schedule for the day in question. This was then applied to each of the one hundred individual households, and along with household elasticity and appliance use values, dictated the extent of the changes in the base case demand that would occur within each household.

The results were divided into those which could be examined at a community/system-wide level, and those which related to household level impacts. The results were also analysed according to household size, household elasticity levels and household appliance use levels. The results of each of the thirty six simulations were then presented and discussed in detail.

Overall, the results show that the use of variable energy pricing in SAHES can result in modest yet significant levels of demand response both at a community and at a household level. An improvement in the match between demand and renewable supply profiles was observed in thirty of the thirty six simulations conducted (83%).

9.1.8 The identification of key factors

Chapter 8 presented the sensitivity analyses which were conducted in order to gain further understanding of the variables which impact on the results obtained in Chapter 7.

The twin aims of these analyses were the identification of the key variables which play a role in facilitating DR, and to account for some of the primary sources of uncertainty and potential inaccuracy associated with the original model results. This created a set of results which has a greater degree of resilience than those achieved through the original modelling process alone.

Both the amount and the extent of DR were found to vary under an alternative renewable energy system specification which included a higher degree of intermittent renewable generation. This was achieved by removing hydro power from the list of available technologies, which in turn resulted in increased amounts of wind generation. Interestingly, the impact of these changed was limited enough to suggest that the developed variable pricing strategies would be effective under a range of supply scenarios, and more specifically in SAHES with predominantly stochastic forms of renewable energy generation.

Price elasticity of demand values and the ratio between maximum and minimum prices were easily identifiable as key variables, given the makeup of the model itself. However, the sensitivity analyses provided valuable insight into the extent to which changes in these variables impacted upon levels of demand response. Despite being sensitive to changes in both demand elasticity and pricing ratios, the results varied predictably and to a limited extent. This suggests that the results of the model - and crucially the general conclusions that can be drawn from them - could reasonably be expected to be transferrable to other contexts and scales. As such, the SAHES model and the variable energy pricing strategies developed therein could be deemed to be worthy of further investigation in other contexts and at different scales.

Interestingly, the sensitivity analyses also found that household energy bills were relatively insensitive to changes in elasticity, meaning that limited financial motivation is provided to consumers to engage in more flexible behaviour. Within the context of this project this can be considered to be a negative result, given that financial incentive is seen as the primary form of motivation for consumer engagement. This points to the need for additional financial incentives to be incorporated into variable pricing tariffs, with the aim of providing (or even guaranteeing) financial reward in return for participation/engagement.

9.2 Contributions to Knowledge

In addressing the primary research question, this thesis has made novel contributions to the field in a number of areas.

- The demonstration of the potential of stand-alone energy systems and remote/isolated communities and their role in the transition from a centralised to a decentralised energy model is a key underlying premise to the thesis, and represents arguably its most significant contribution to knowledge.
- A targeted domestic consumer survey, gauging consumers' understanding of energy issues and their attitudes towards demand flexibility and the use of enabling technology. This also includes a study of how attitudes and understanding of energy issues vary with the degree of urbanisation of communities.
- The development of a bottom-up, disaggregated, high resolution, community domestic energy consumption model, which is representative of the type of community in which SAHES are typically deployed. This model includes three demand response algorithms designed to facilitate consumer response to energy price variation.
- The identification of extreme short-term demand elasticity as a highly relevant factor in the use of variable energy pricing, and of the need for further research into the area.
- The development of three conceptual variable energy pricing strategies, all based upon renewable generation output.
- An assessment of the impact of the introduction of variable energy pricing in SAHES both at a community and at a household level, including a number of sensitivity analyses which further examine the resilience of the developed strategy and the sensitivity of the results to variation in key input parameters.

9.2.1 Recommendations

The implications of the research findings and contributions to knowledge discussed above can be translated into a number of recommendations, with a view to informing future research and policy discussion.

The first and most important recommendation surrounds the support for variable pricing to be applied on a trial basis in real world SAHES. While this research has provided a proof of concept, a much more detailed understanding of how variable pricing can/should be applied in real projects is required. This requires further research (see section 9.3), but will ultimately require testing on a real world SAHES. This will require a supportive policy and regulatory environment, and considerable commitment from both academia and industry.

Existing SAHES projects have largely had to rely on highly motivated community groups and considerable industrial input to overcome the various financial and regulatory obstacles which result from the current lack of a supportive policy environment. The highly case specific nature of these projects appears to contribute to this issue, making the task of providing support which is general enough to be broadly applicable yet specific enough to be tailored to each specific instance, a very difficult one. This is likely to be an issue when it comes to the implementation of variable pricing too. Policy makers must continue to address these issues if the targets intended to deliver a sustainable energy future are to be met. Ideally, framework policies would adopt an innovative and *proactive* approach in order to support real world trials, rather than the *reactive* approach which has been prevalent in recent years when it comes to SAHES.

Despite increasing interest in the concept of variable domestic energy pricing, there is much still to be learnt by industry, governments, regulators and academia. Existing SAHES projects, and the communities behind their emergence, are often at the forefront of innovation in this area, and therefore represent a significant resource. Transparency and the sharing of findings and information between the various stakeholders is therefore considered essential if the experiences and outcomes from these early examples are to be built upon.

9.2.2 Limitations

This research has provided a broad-ranging proof of both the concept and context for the application of variable domestic energy pricing in SAHES. However, a number of limitations must be acknowledged.

Firstly, the range and variety of variables which were included in the development of the SAHES demand model, the DR algorithms and the SAHES sizing and specification meant that exhaustive analysis of all possible scenarios and results was not possible. It therefore must be acknowledged that while the results presented cover the most likely scenarios and variables, all potential scenarios and variables have not been analysed in depth. Similarly, the need for this research to maintain a balance between providing general (and therefore widely applicable) results and ensuring that the results remain detailed enough to be informative meant that certain aspects of SAHES which are location specific, such as local consumer attitudes, appliance ownership levels, renewable energy resources etc., were not fully explored.

The pricing strategies presented are conceptual only, and are unlikely to reflect the type of strategy/tariff that may be used in real world applications. This research also does not examine the costs associated with implementing or administering variable pricing in SAHES, or fully quantify the resulting capital savings or the overall cost-effectiveness of such an approach. This would require a more detailed, project specific approach.

Due to the focus on proof of concept, this research has deliberately avoided any specific details of the type of enabling technology which can/should be used to help consumers enact DR.

There are also elements of the DR algorithms used in this research which may not reflect actual domestic DR accurately. These include:

- the selection of shiftable, curtailable and growable appliance loads
- the order in which loads are shifted/curtailed/grown
- the temporal extent to which loads can be shifted
- the consumer price elasticity of demand values used

While the approach used has been based and justified on literature and relevant consumer statistics, all of the variables may prove different in practice. Indeed, aspects of the model such as appliance use and community-wide elasticity levels are likely to be among those variables which can be thought of as being highly project/site specific.

The potential role of recently and currently emerging technologies - namely Plug-in Hybrid Electric Vehicles and domestic batteries - in impacting/facilitating domestic DR has been excluded from the scope of this research due to the level of complexity and uncertainty that their inclusion would bring to the project. Such technologies, however, are the subject of much research and development at present, and their contribution to the field of domestic DR is potentially significant. As such, this is an area which is identified as being in need of further research, as discussed in the following section.

Lastly, it is also important to reiterate the limitations associated with the consumer attitudes survey, the findings of which were presented in Chapter 5. These include the limitations to the representativeness of results which are the product of a web-based, chain-referral sampling methodology. The use of self-reporting also has the potential to create results which do not materialise in practice. Further, more in-depth analysis into the attitudes of domestic consumers in remote and isolated communities is therefore required (this is also discussed further in the following section).

9.3 Future Work

The work presented in thesis has provided an examination of the viability of using renewable generation as the basis for variable domestic energy pricing in stand-alone hybrid energy systems. This work could provide a suitable foundation for a number of further research activities.

9.3.1 Model refinement

The first and most obvious opportunity for further work relates to the development of the models and algorithms presented in this thesis. This could also be seen as addressing the limitations associated with the approach taken.

One of the main challenges associated with conducting research within the context of remote and isolated communities is the project and locale-specific nature of both energy consumption and energy generation possibilities. However, the bottom-up demand model presented could be replicated to suit the conditions at any particular location or community. A finer timestep resolution would also provide a more accurate reflection of how the implementation of variable pricing would work in real time. By reducing the timestep duration, it follows that the response of consumers to energy pricing variations will become more reliant on enabling technology.

The approach described in this thesis places emphasis on the viability, design and impact of variable pricing in SAHES. However, a more detailed approach could usefully include consideration of power systems engineering factors such as frequency regulation, voltage control, network topology and operational factors.

Further research could also be conducted into the suitability of various low and zero carbon technologies for use in conjunction with variable pricing, and the compatibility of different variable pricing approaches with energy system characteristics, such as the proportion of intermittent generation and levels of energy storage used.

This thesis identifies the importance of control and metering technology to facilitate short-term and extreme short-term demand response. The research into the design and implementation of this technology continues at pace. Thus far, the primary driver of this research - namely the upcoming widespread deployment of smart metering - has guided the development of this technology in a direction which is also conducive to its use within the context of SAHES. However, such is the potential of this emerging field, an element of SAHES-specific research and development would also be highly beneficial. Specifically, this should include the development and implementation of load control and shifting strategies, and place focus on accommodating consumer preferences and facilitating their real-time interaction with energy pricing in an unobtrusive manner.

This thesis has presented three approaches to variable energy pricing which have been adapted from conventional forms of variable pricing. In reality, the development of energy pricing tariffs is a far more complex endeavour, with many variables and influences affecting the final design and implementation. Therefore, if the used of variable pricing in SAHES is to be investigated in more detail, a more detailed approach is likely to be required.

The future development of such pricing strategies should also address more directly the potential for “free-rider” behaviour, either through a more sophisticated pricing structure which ensures DR engagement is always rewarded, or through a mechanism which is separate from the pricing structure altogether.

When it comes to assessing the disruption to households caused by DR, further work is also required. This should take the many different behavioural factors affecting perceived disruption and inconvenience into account, and should reflect the varying levels of disruption caused by the alteration of different appliance loads e.g. the shifting of an electric water heating load compared with the curtailment of a television load.

9.3.2 The role of Plug-in Hybrid Electric Vehicles

This thesis has not specifically addressed the emerging and considerable potential impact of Plug-in Hybrid Electric Vehicles. If charged domestically, these would have a huge impact upon domestic energy consumption patterns. If utilised as shiftable loads, the potential ramifications for domestic demand response could be profound. As such, this is an area which is deemed worthy of further investigation.

9.3.3 Detailed quantification of consumer elasticity

In discussing the key factors affecting the potential viability of variable domestic energy pricing, this thesis has identified the importance of the response of consumers over the extreme short-term i.e. at hourly or sub-hourly timesteps. This concept is made relevant by the recent emergence of enabling technology, and as such would benefit from further research. This should include attempts to quantify extreme short-term elasticity among different consumer groups, and the identification of factors which differentiate it from longer-term elasticity.

Models such as the one presented in this thesis could usefully move beyond elasticity estimates (which are used as a proxy for consumer response/behaviour) towards a more holistic approach to accounting for consumer response to price variation. In particular, this could usefully include further investigation into the long-term sustainability of applying variable energy pricing in the way presented in this study. A more holistic approach is likely to benefit from the continued study of behavioural change within the field of domestic energy consumption. This is seen as an area of great importance, as the understanding of how consumers respond to energy price variations is fundamental to the design, implementation and ultimate success of variable energy pricing schemes in any context.

9.3.4 Trial deployment

The energy generation, consumption and pricing models presented in this thesis serve as an initial investigation into the potential for variable pricing to be used within the context of SAHES. Further steps, such as those outlined above, relate to the refinement of this approach and a furthering of the investigation into the viability of such an approach being used in the real world. If this can be established from a theoretical perspective, the next step would logically involve a trial deployment in a real world application(s). Only then could the approach be subjected to the many variables and constraints associated with the context, and its viability verified and tested fully. As with many new and pioneering approaches relating to SAHES, remote and isolated communities are likely to be the test bed for such a trial deployment. Encouragingly, the existence of alternative energy pricing schemes such as that adopted on the island of Eigg (as discussed in Chapter 6) indicate that such a trial deployment could be a viable proposition in the near future.

9.4 Summary

This thesis has presented an investigation into the use of variable energy pricing to achieve domestic demand response in stand-alone hybrid energy systems. It has presented a detailed review of the relevance of this field of research, and has presented the results of a consumer survey in order to establish the viability of such an approach. A representative SAHES model based on the outcomes of this research has also been presented. This model uses a range of consumer price elasticity of demand values as a proxy for consumer response to price variation, and reflects a range of attitudes and domestic consumption patterns. Three conceptual variable energy pricing approaches have been developed, based on conventional forms of variable energy pricing. These have then been applied to the SAHES model, and the results presented and discussed in terms of the impact at both consumer and community level. The resilience of these results has also been examined through a number of sensitivity analyses focussing on key areas of uncertainty which are inherent within the SAHES model. These results have shown the use of renewable energy generation as the basis for domestic energy price variation to be fundamentally viable.

In doing so, the project has successfully completed the objectives set out, and has made a contribution to knowledge in a number of useful areas, which can inform the future development of SAHES.

Appendix A: Consumer Attitudes Survey Transcript

--- Transcript Begins ---

About your home.

Q1 Please enter your post code:

NOTE: This will be used to define the geographical location of your home only, and not for postal use. This information (as with all information supplied in this survey) will remain strictly confidential. If you have any reservations or questions about supplying this information, please feel free to contact the research team using the details provided.)

Q2 Select which of the following best describes your community?

- ❍ Urban
- ❍ Suburb
- ❍ Rural
- ❍ Remote or isolated community

Q3 How many people live in your home on a permanent basis?

Q4 Which of the following is the primary fuel used to heat your house?

- ❍ Mains gas
- ❍ Bottled gas
- ❍ Electric heaters
- ❍ Liquid fossil fuel (e.g. red diesel, fuel oil etc, LPG)
- ❍ Wood fuel
- ❍ Heat pump (electric)
- ❍ Solar water heating
- ❍ Other (please specify) ____________________
- ❍ Don't know

Q5 Which of the following energy tariffs is your home currently on? (NOTE: For an explanation of the various tariff types, please click here: ("http://www.which.co.uk/switch/energy-advice/energy-tariffs-explained"))

- ❍ Dual fuel tariff
- ❍ Capped tariff
- ❍ Fixed tariff
- ❍ On-line tariff
- ❍ Economy 7 / Economy 10
- ❍ Prepayment meters
- ❍ Green energy tariff
- ❍ Independent Gas Transporter tariff
- ❍ Social energy tariff
- ❍ Other (please specify): ____________________
- ❍ Don't know

Energy Attitudes.

Q6 How would you rate the importance of energy supply in comparison to other social issues such as education, healthcare and the economy?

❍ Very low priority

❍ Low priority

❍ Middle priority

❍ High priority

❍ Very high priority

Q7 Please define the extent to which you consider the following in your everyday life:

	Never	Rarely	Occasionally	Often	Every day	Multiple times a day
Energy consumption	❍	❍	❍	❍	❍	❍
Water consumption	❍	❍	❍	❍	❍	❍
Waste production	❍	❍	❍	❍	❍	❍

Q8 How would you rate your knowledge of energy issues i.e. your understanding and appreciation of the energy supply system, how it works, and the challenges associated with it?

❍ Much lower than average

❍ Significantly lower than average

❍ Slightly lower than average

- Average
- Slightly higher than average
- Significantly higher than average
- Much higher than average

Q9 How do you think your household's energy consumption would compare to a typical household of a similar size?

- Much lower than average
- Significantly lower than average
- Slightly lower than average
- Average
- Slightly higher than average
- Significantly higher than average
- Much higher than average

Your attitude towards Demand Response

Demand response is a term used to describe adjustments made to energy consumption, by altering either the timing or the amount of consumption. These adjustments would typically be made in response to changes in the price of energy, and would occur either as a result of voluntary consumer action, or via automated control technology. For example, a price increase during a certain time of day could lead to consumers reducing their demand during that time, or waiting until later to consume energy.

Q10 Would you be willing to alter your energy consumption in the way described above?

- ❍ Yes
- ❍ No

Q10b *Logic: If "Would you be willing to alter your energy consumption in the way described above?" is answered 'No'*

You answered 'No'. Please explain the reasons for your answer:

Q10b *Logic: If "Would you be willing to alter your energy consumption in the way described above?" is answered 'Yes'*

Shown below are a series of possible motivations for adjusting energy consumption. Please click and drag to rank these in order of importance.

______ Achieving (minor) financial savings

______ Reducing my environmental impact

______ Contributing to the efficient operation of the wider energy supply system

______ Other (please specify):

Q11 Would you consider using (cost-effective) technology to automatically adapt your energy consumption pattern?

- ❍ Definitely not
- ❍ Only if its effect was undetectable during everyday use
- ❍ Yes, even if some restrictions were required
- ❍ Yes, no matter what restrictions were required

Q11b *Logic: If "Would you consider using (affordable) technology to automatically adapt your energy consumption pattern?" is answered 'Definitely not'*

You answered 'Definitely not' for Q10 Please explain the reasons for your answer.

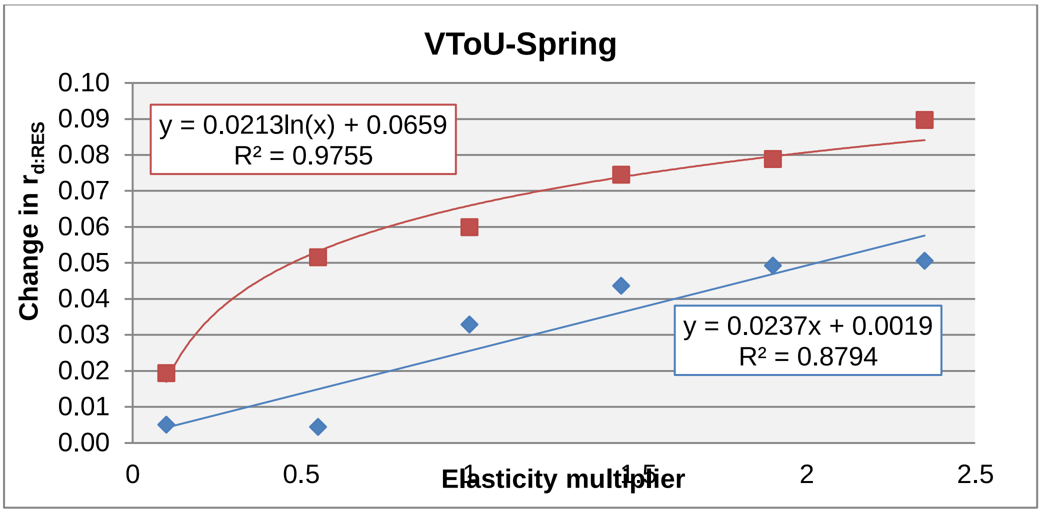
--- Transcript Ends ---

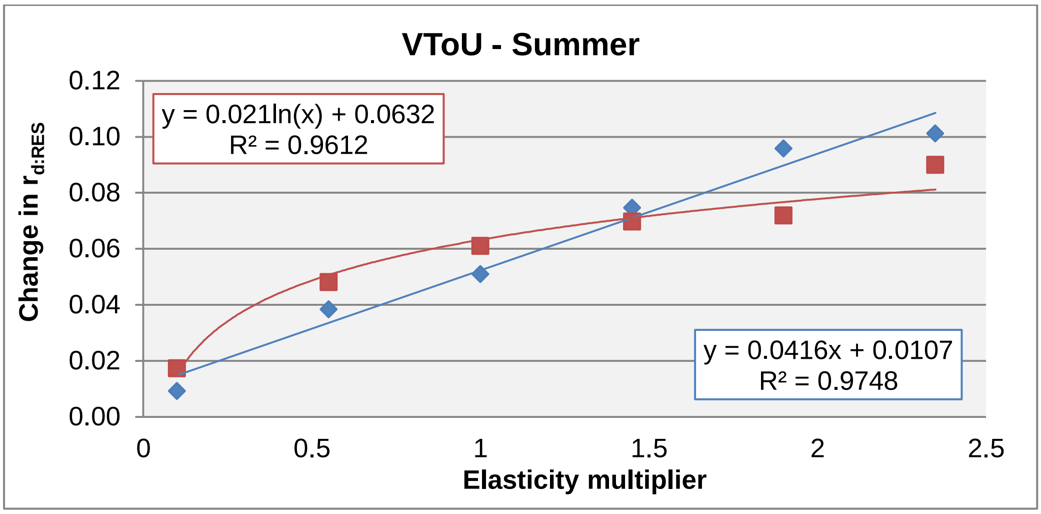
Appendix B: Sensitivity Analysis Results

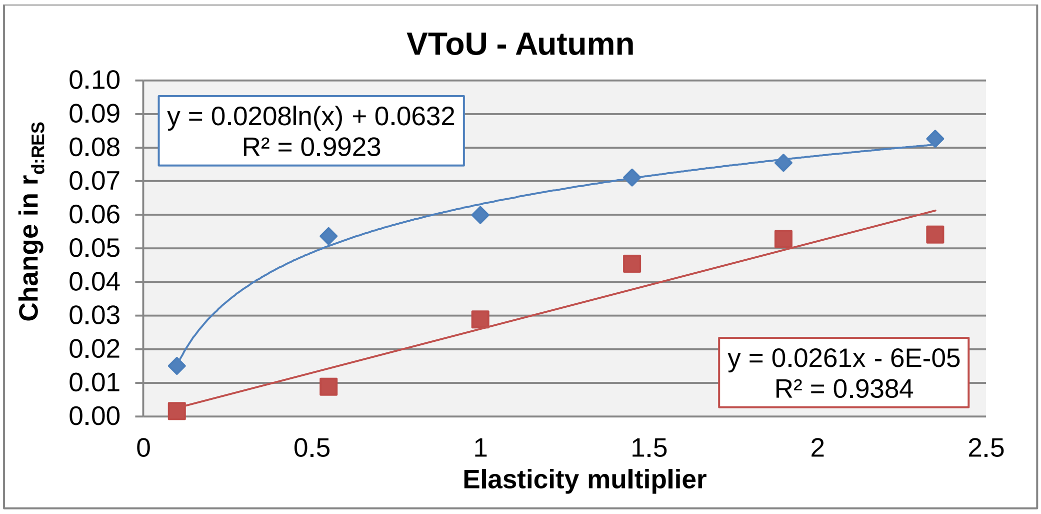
This Appendix presents the results of all the sensitivity analyses presented in Chapter 8. As the alternative Renewable Energy Supply Scenario results were presented in full, these results are not included herein.

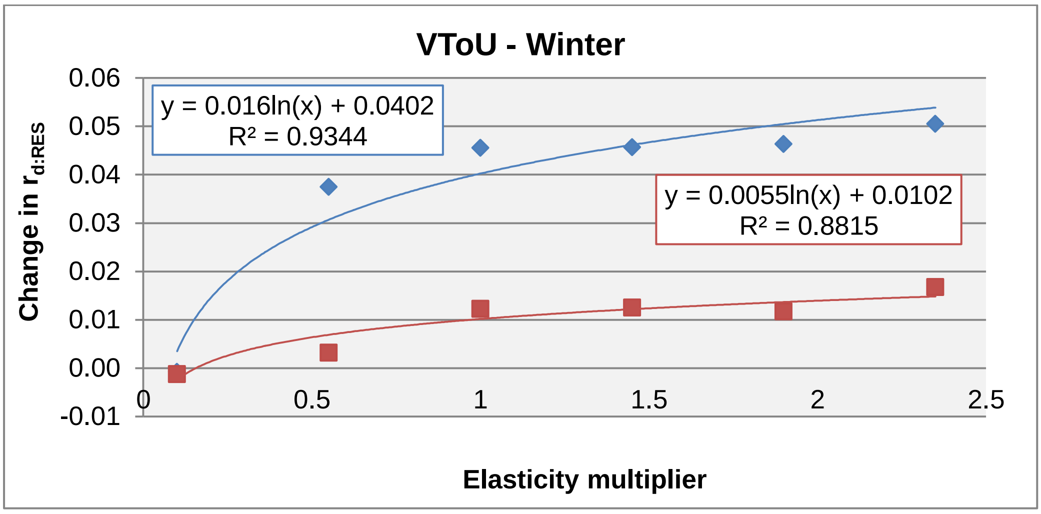
9.1 Sensitivity Analysis 2: Consumer Price Elasticity of Demand

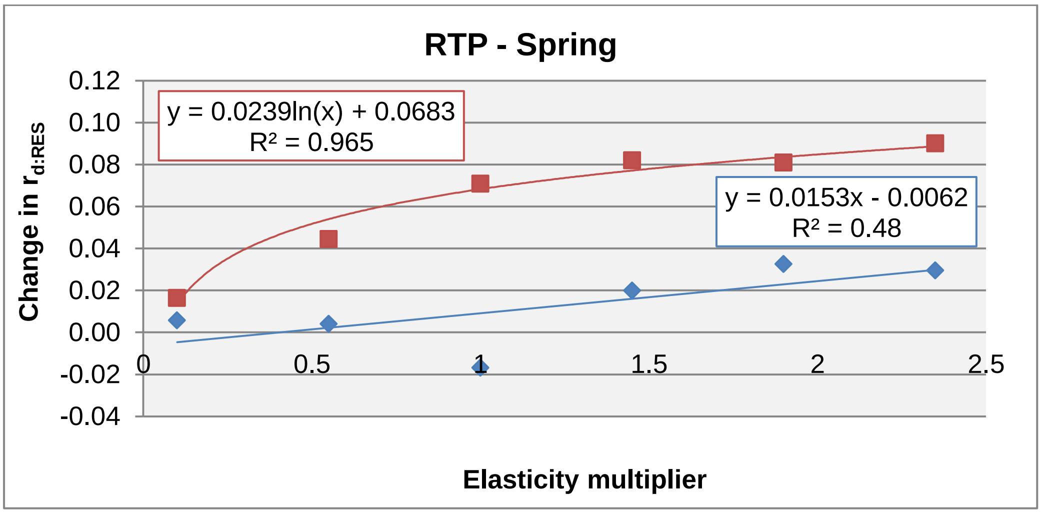
Change in $r_{d:RES}$

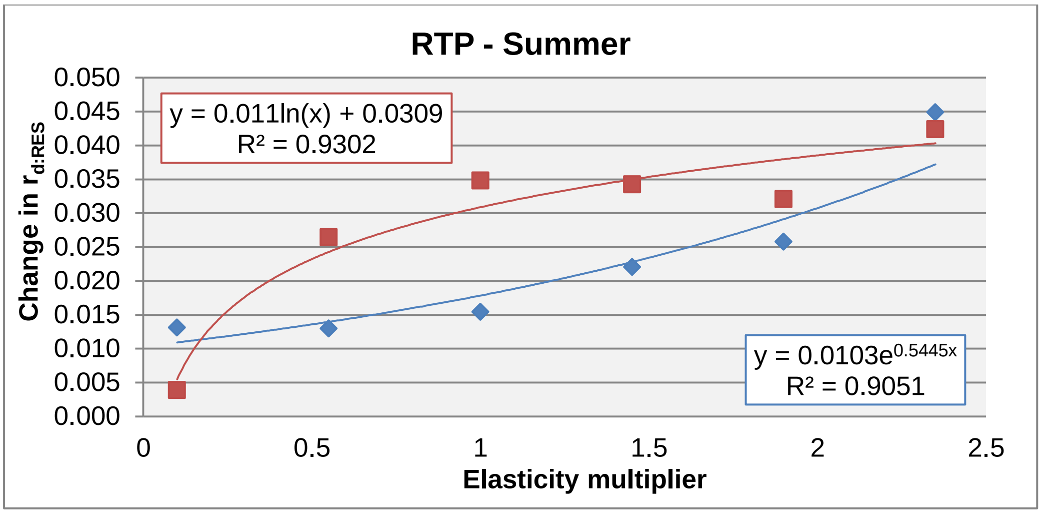


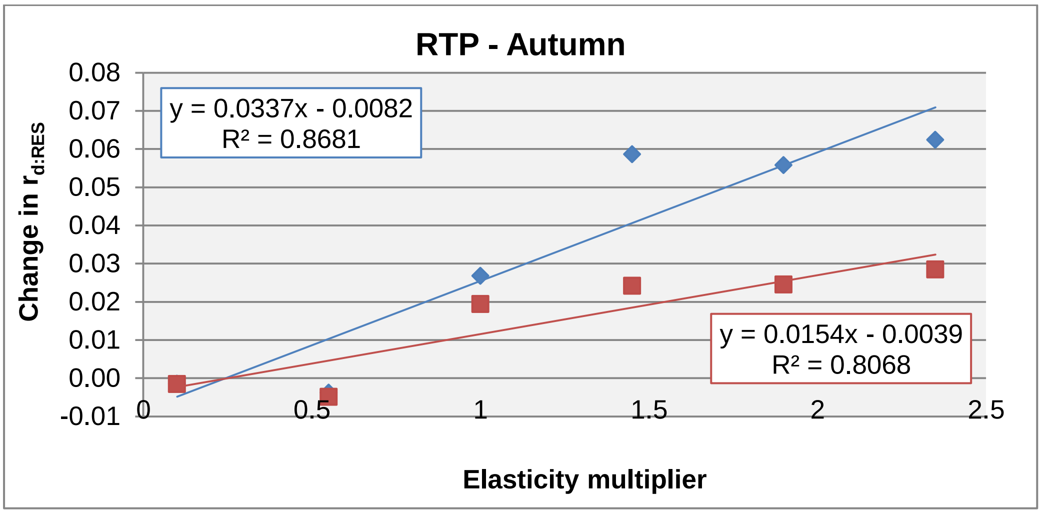


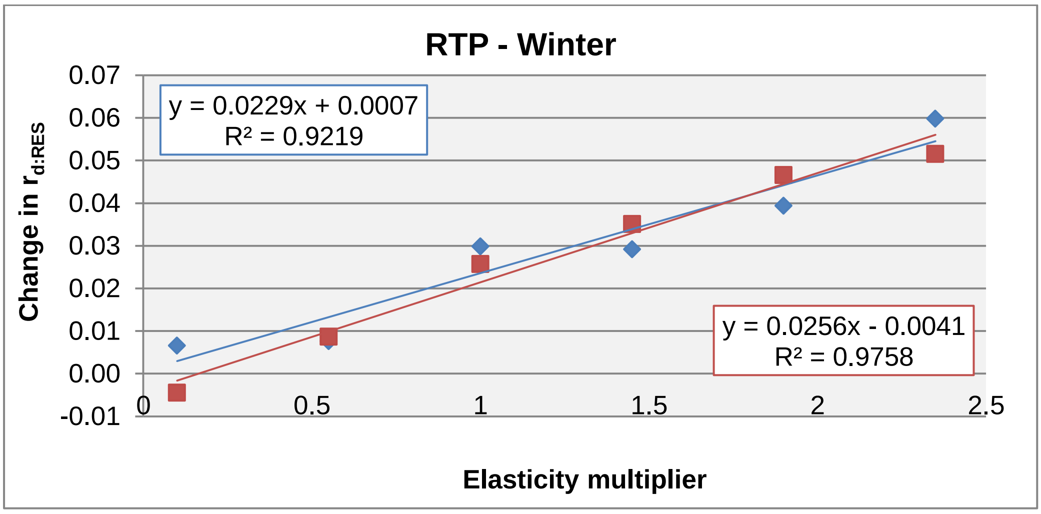

VToU - Autumn
y = 0.0208ln(x) + 0.0632
R² = 0.9923
y = 0.0261x - 6E-05
R² = 0.9384
Change in r d:RES
Elasticity multiplier
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
0.5
1
1.5
2
2.5

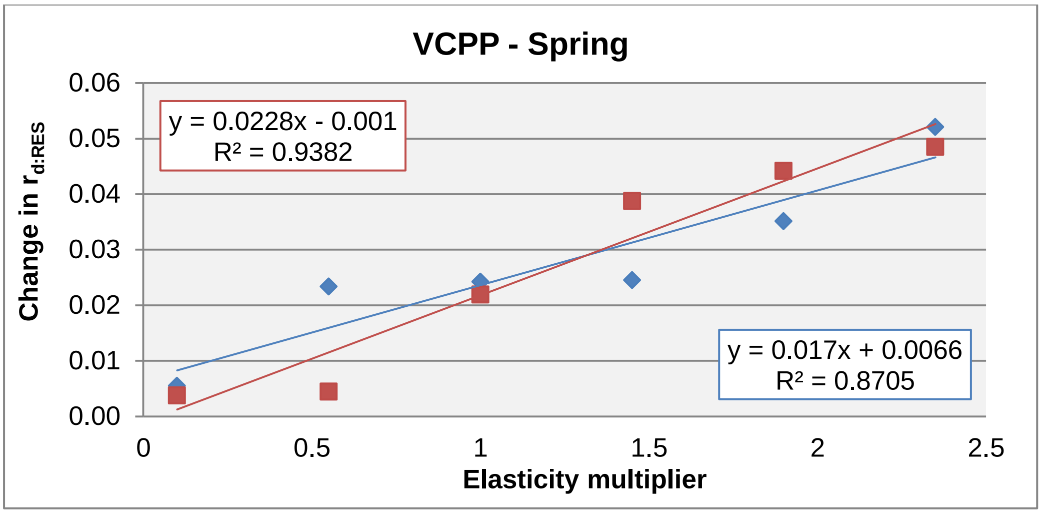

VToU - Winter
y = 0.016ln(x) + 0.0402
R² = 0.9344
y = 0.0055ln(x) + 0.0102
R² = 0.8815
Change in r d:RES
Elasticity multiplier
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
0
0.5
1
1.5
2
2.5

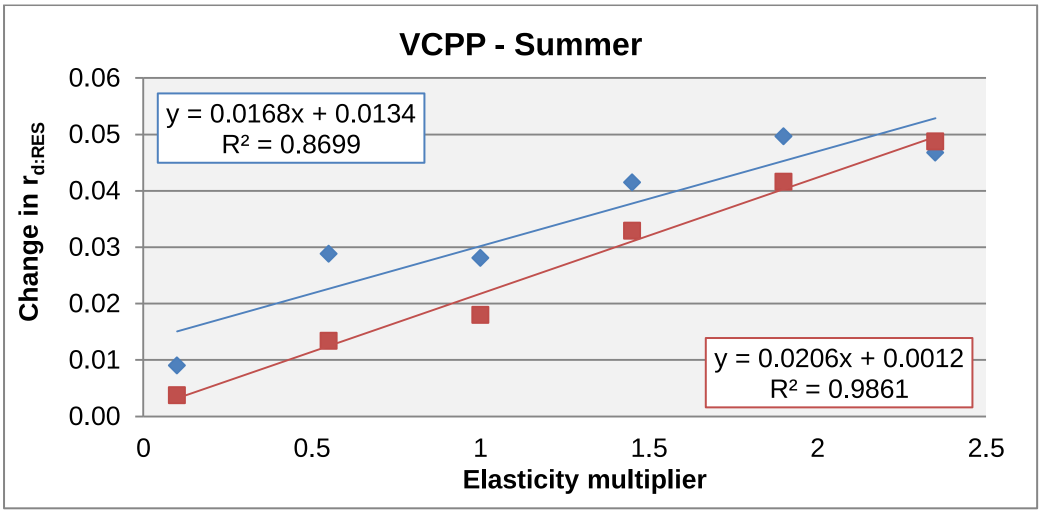

RTP - Spring
y = 0.0239ln(x) + 0.0683
R² = 0.965
y = 0.0153x - 0.0062
R² = 0.48
Change in r d:RES
Elasticity multiplier
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
0
0.5
1
1.5
2
2.5

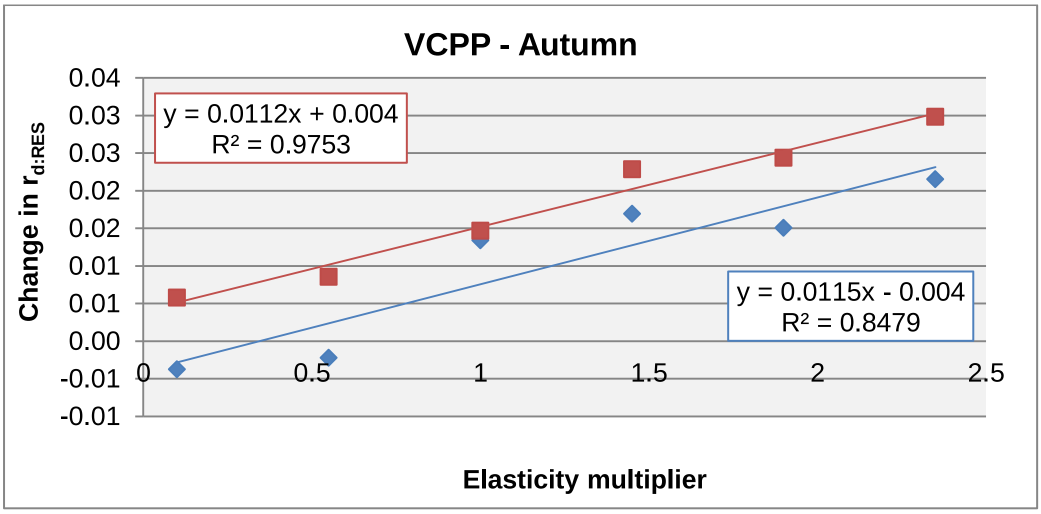

RTP - Summer
Change in r d:RES
0.050
0.045
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
y = 0.011ln(x) + 0.0309
R² = 0.9302
y = 0.0103e^0.5445x
R² = 0.9051
0
0.5
1
1.5
2
2.5
Elasticity multiplier

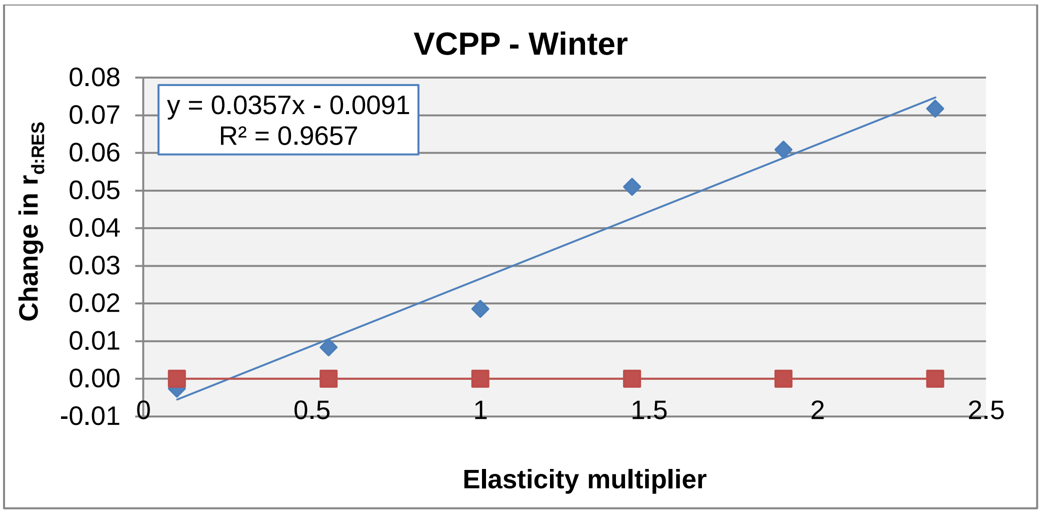

RTP - Autumn
Change in r d:RES
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
y = 0.0337x - 0.0082
R² = 0.8681
y = 0.0154x - 0.0039
R² = 0.8068
0
0.5
1
1.5
2
2.5
Elasticity multiplier


RTP - Winter
Change in r d:RES
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
y = 0.0229x + 0.0007
R² = 0.9219
y = 0.0256x - 0.0041
R² = 0.9758
0
0.5
1
1.5
2
2.5
Elasticity multiplier

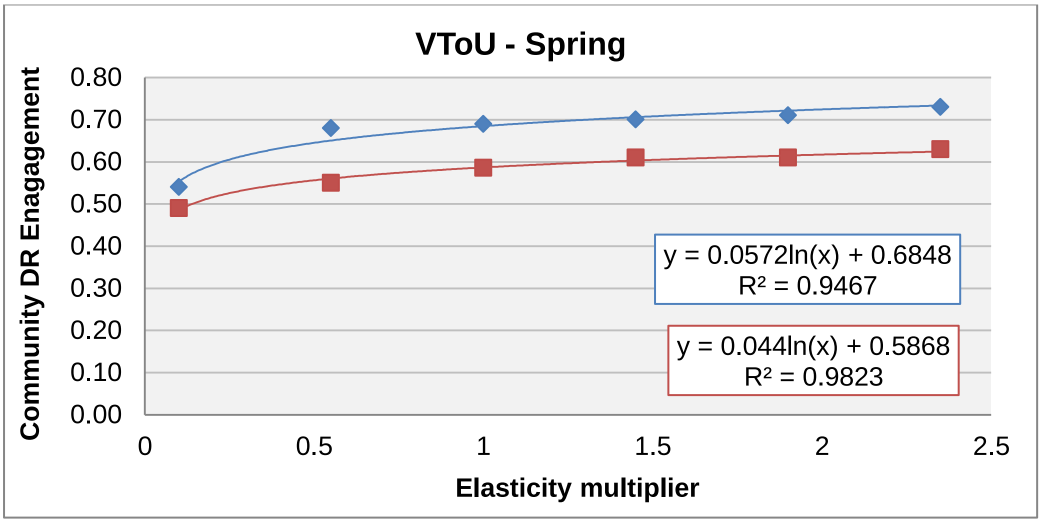

VCPP - Spring
y = 0.0228x - 0.001
R² = 0.9382
y = 0.017x + 0.0066
R² = 0.8705
Change in r d:RES
Elasticity multiplier
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
0.5
1
1.5
2
2.5

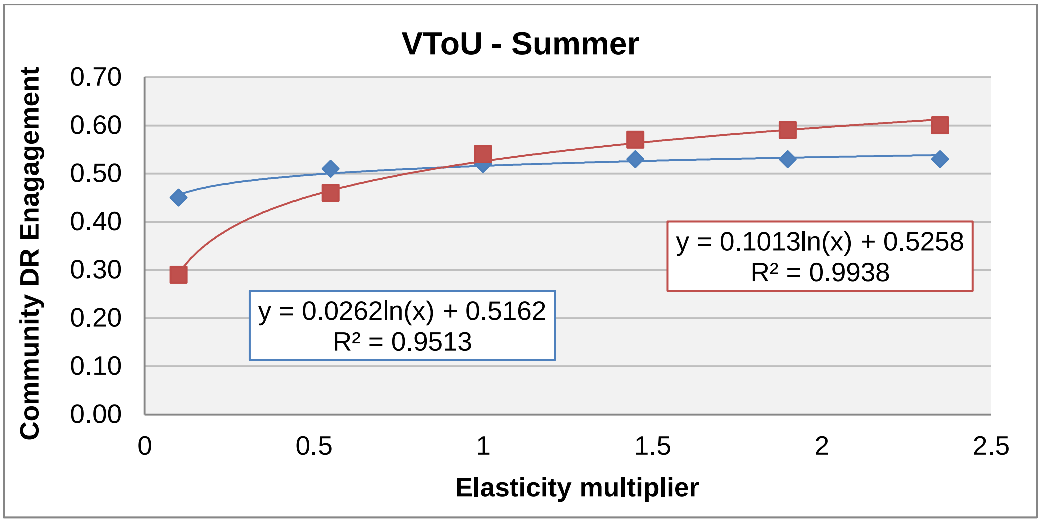

VCPP - Summer
y = 0.0168x + 0.0134
R² = 0.8699
y = 0.0206x + 0.0012
R² = 0.9861
Change in r d:RES
Elasticity multiplier
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
0.5
1
1.5
2
2.5

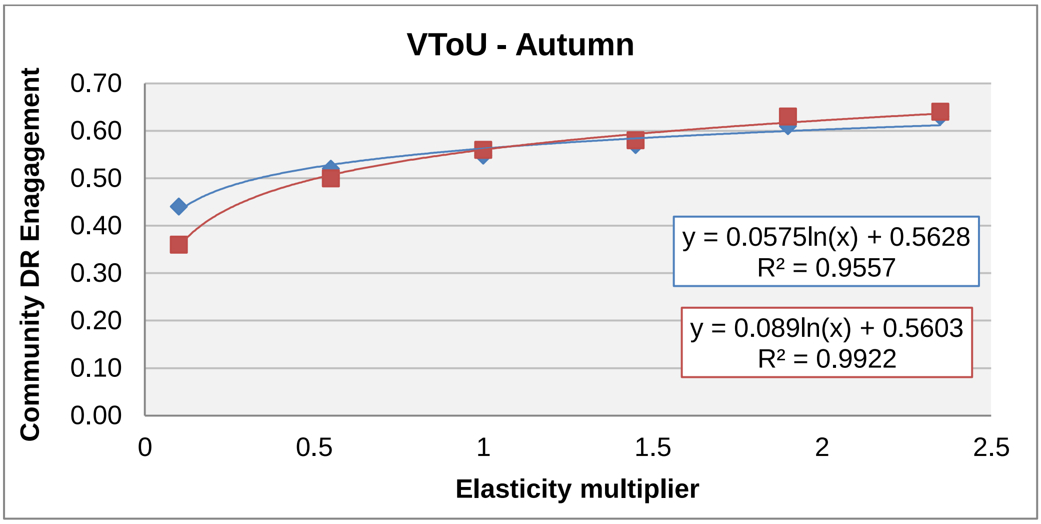

VCPP - Autumn
y = 0.0112x + 0.004
R² = 0.9753
y = 0.0115x - 0.004
R² = 0.8479
Change in r d:RES
Elasticity multiplier
0.04
0.03
0.03
0.02
0.02
0.01
0.01
0.00
-0.01
-0.01
0
0.5
1
1.5
2
2.5

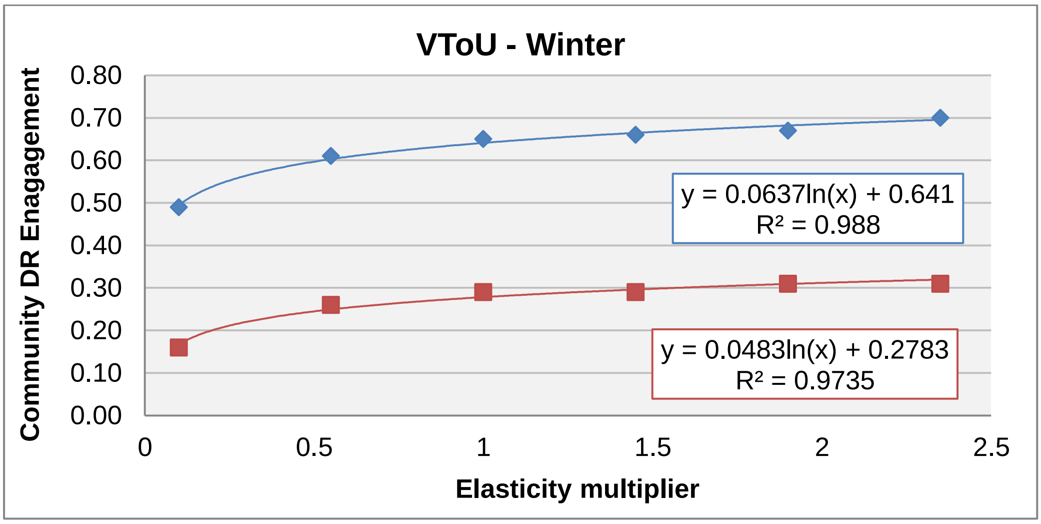


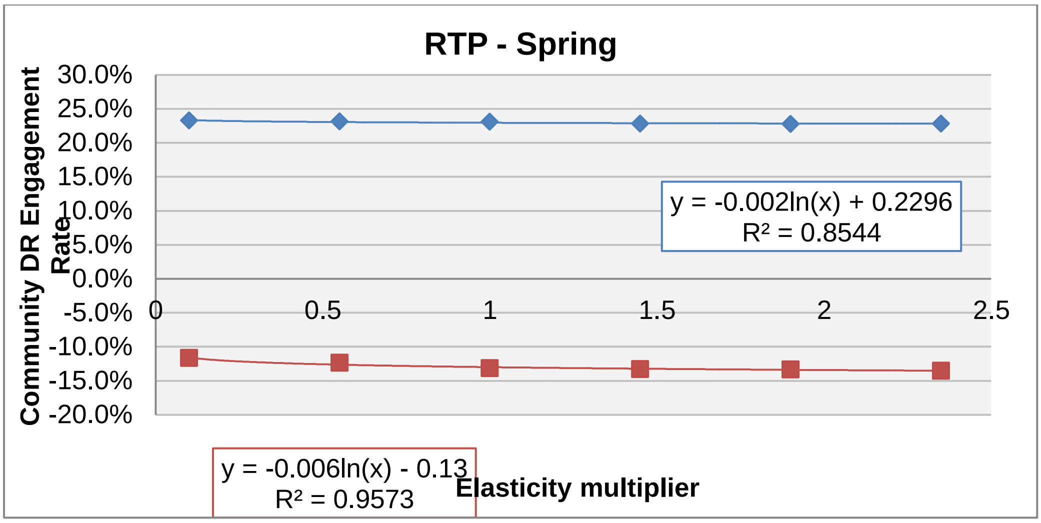
Community DR Engagement:

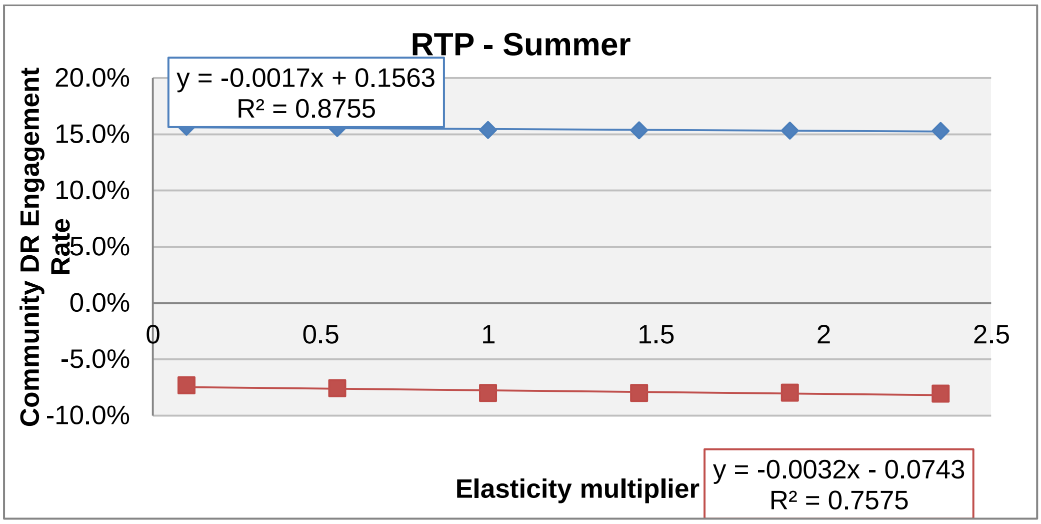


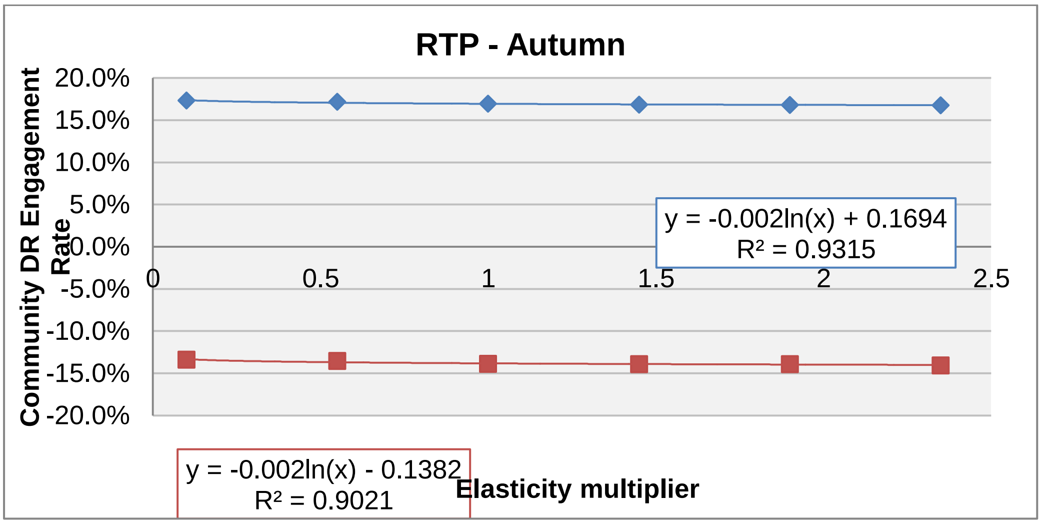

VToU - Summer
Community DR Enagagement
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = 0.1013ln(x) + 0.5258
R² = 0.9938
y = 0.0262ln(x) + 0.5162
R² = 0.9513

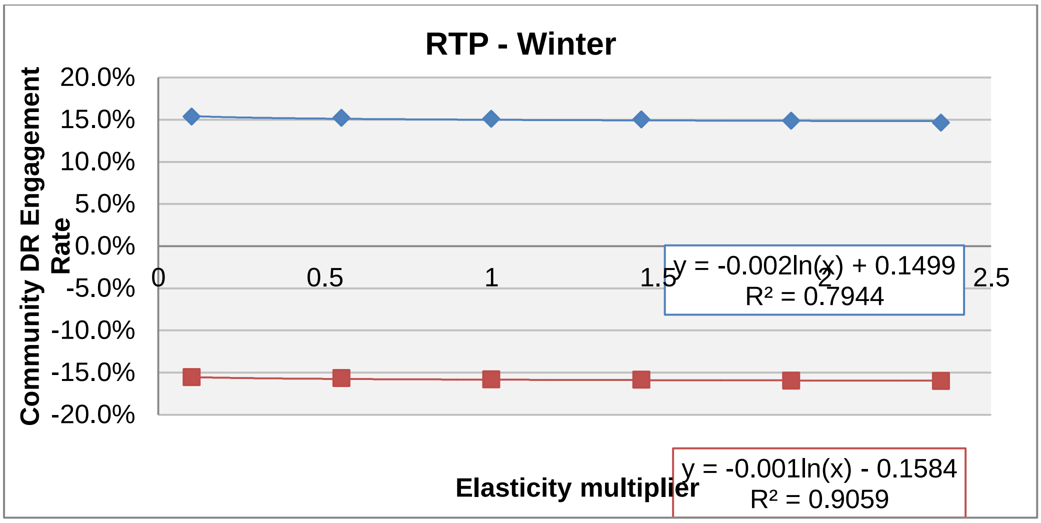

VToU - Autumn
Community DR Enagagement
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = 0.0575ln(x) + 0.5628
R² = 0.9557
y = 0.089ln(x) + 0.5603
R² = 0.9922

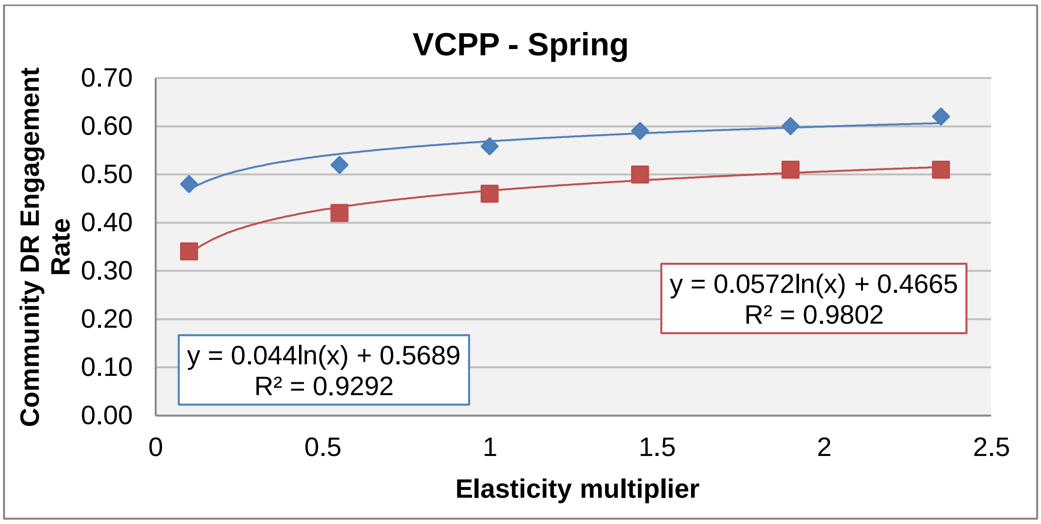

VToU - Winter
Community DR Enagagement
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = 0.0637ln(x) + 0.641
R² = 0.988
y = 0.0483ln(x) + 0.2783
R² = 0.9735

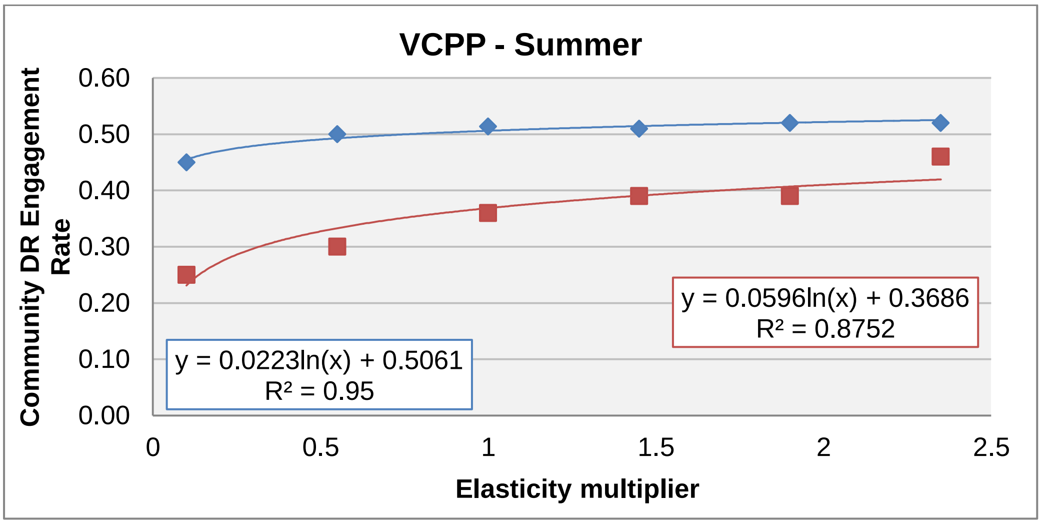

RTP - Spring
Community DR Engagement Rate
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.002ln(x) + 0.2296
R² = 0.8544
y = -0.006ln(x) - 0.13
R² = 0.9573
Elasticity multiplier

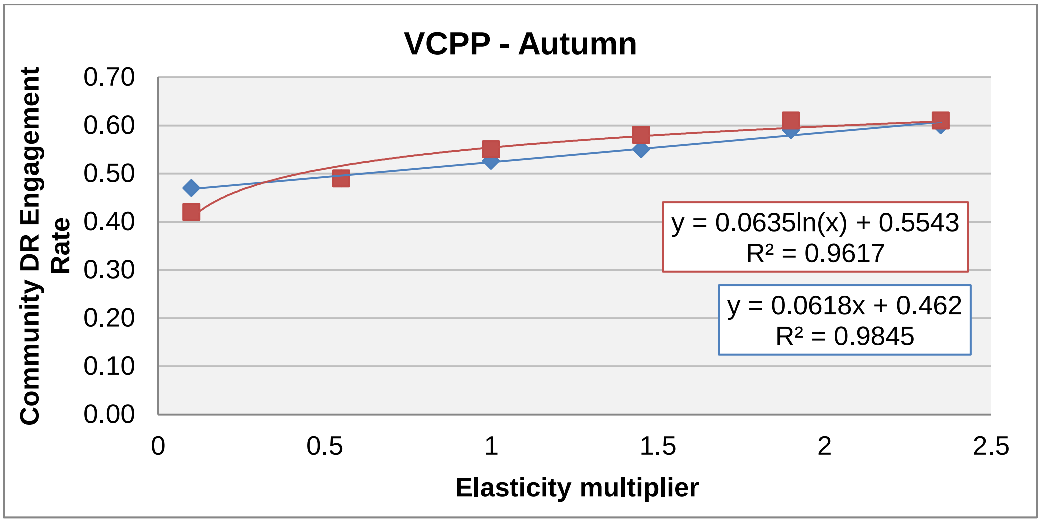

RTP - Summer
Community DR Engagement Rate
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
0
0.5
1
1.5
2
2.5
y = -0.0017x + 0.1563
R² = 0.8755
y = -0.0032x - 0.0743
R² = 0.7575
Elasticity multiplier

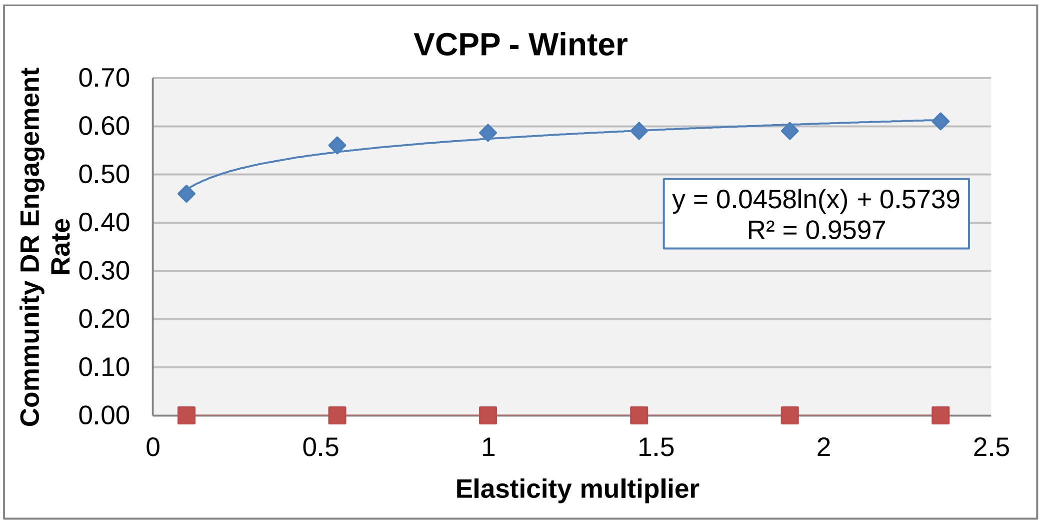

RTP - Autumn
Community DR Engagement Rate
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.002ln(x) + 0.1694
R² = 0.9315
y = -0.002ln(x) - 0.1382
R² = 0.9021
Elasticity multiplier


RTP - Winter
Community DR Engagement Rate
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.002ln(x) + 0.1499
R² = 0.7944
y = -0.001ln(x) - 0.1584
R² = 0.9059
Elasticity multiplier

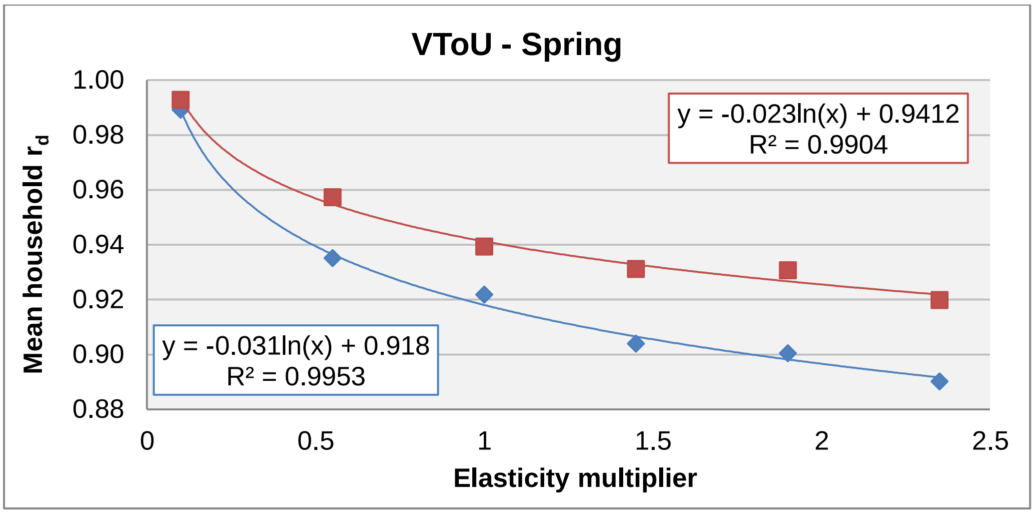

VCPP - Spring
Community DR Engagement Rate
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
0.5
1
1.5
2
2.5
y = 0.0572ln(x) + 0.4665
R² = 0.9802
y = 0.044ln(x) + 0.5689
R² = 0.9292
Elasticity multiplier

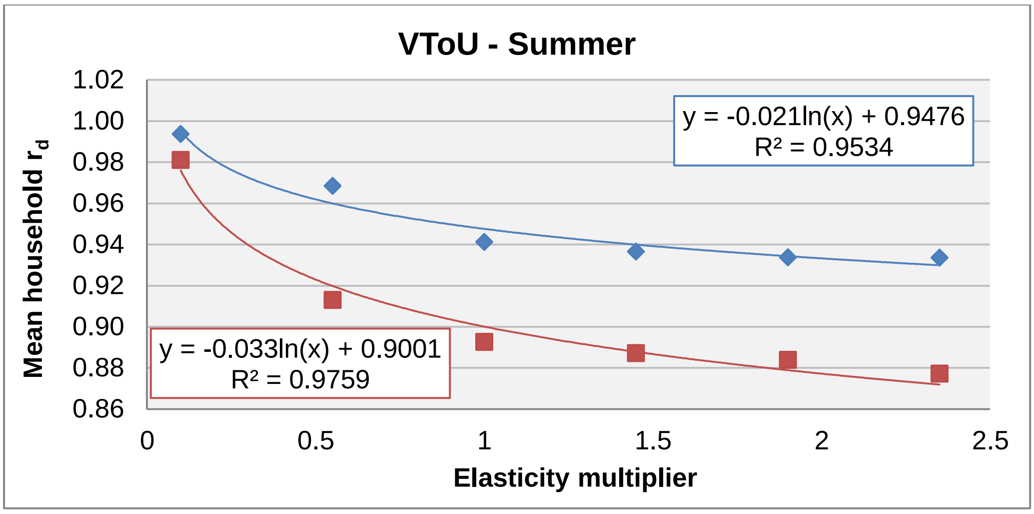

VCPP - Summer
Community DR Engagement Rate
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
0.5
1
1.5
2
2.5
y = 0.0596ln(x) + 0.3686
R² = 0.8752
y = 0.0223ln(x) + 0.5061
R² = 0.95
Elasticity multiplier

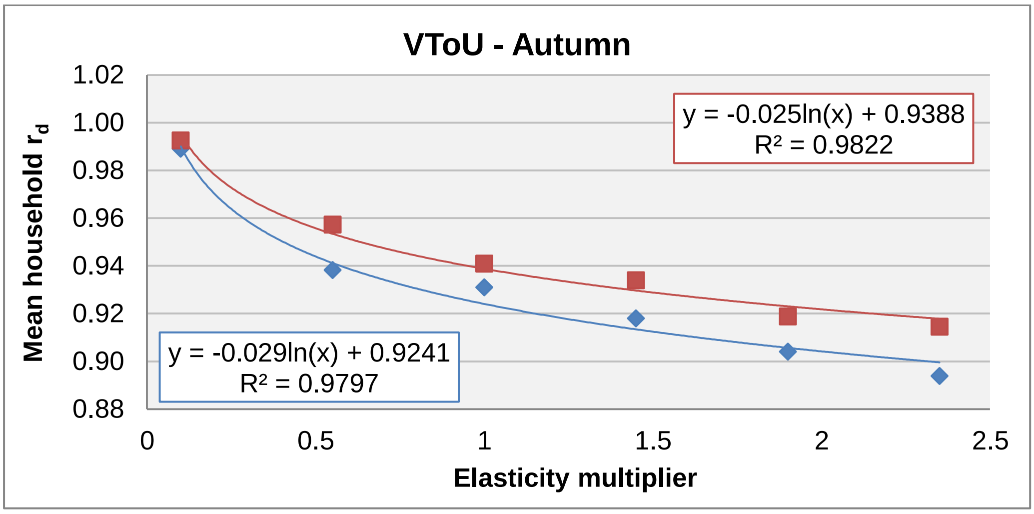


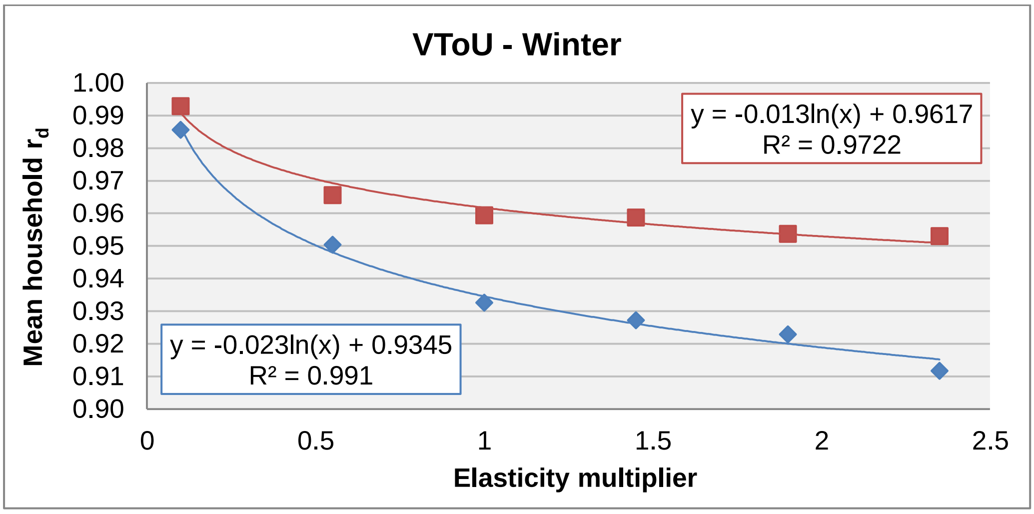


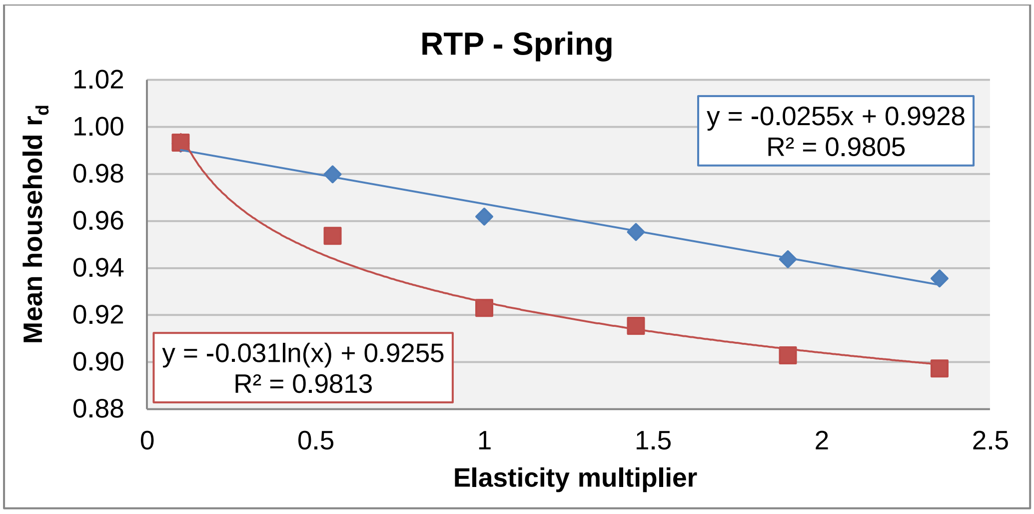
Mean Household r_d:

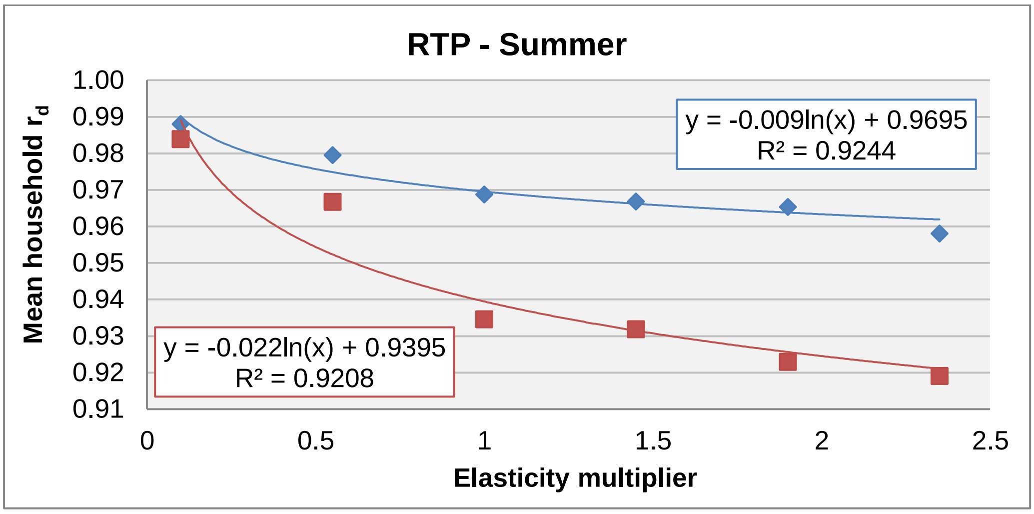


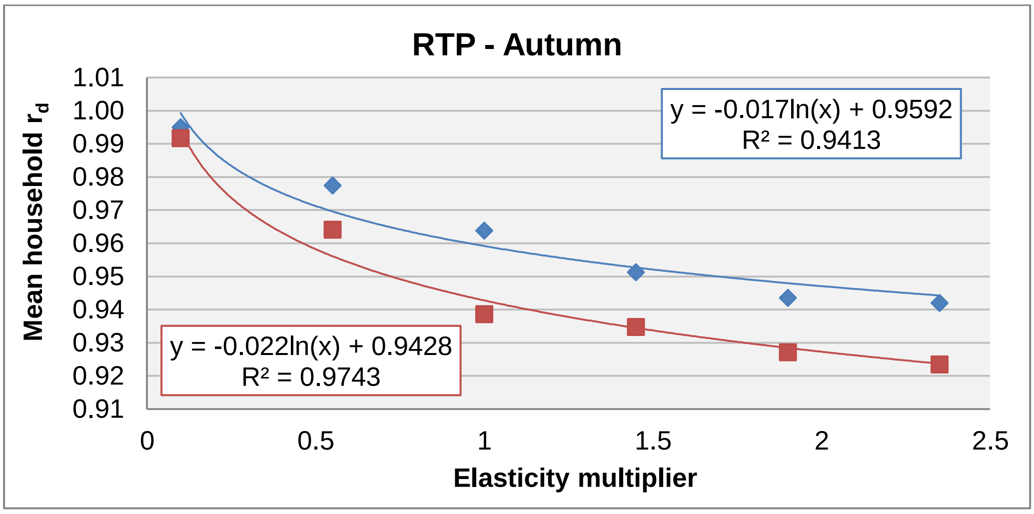

VToU - Summer
1.02
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
Mean household r_d
y = -0.021ln(x) + 0.9476
R² = 0.9534
y = -0.033ln(x) + 0.9001
R² = 0.9759
0
0.5
1
1.5
2
2.5
Elasticity multiplier

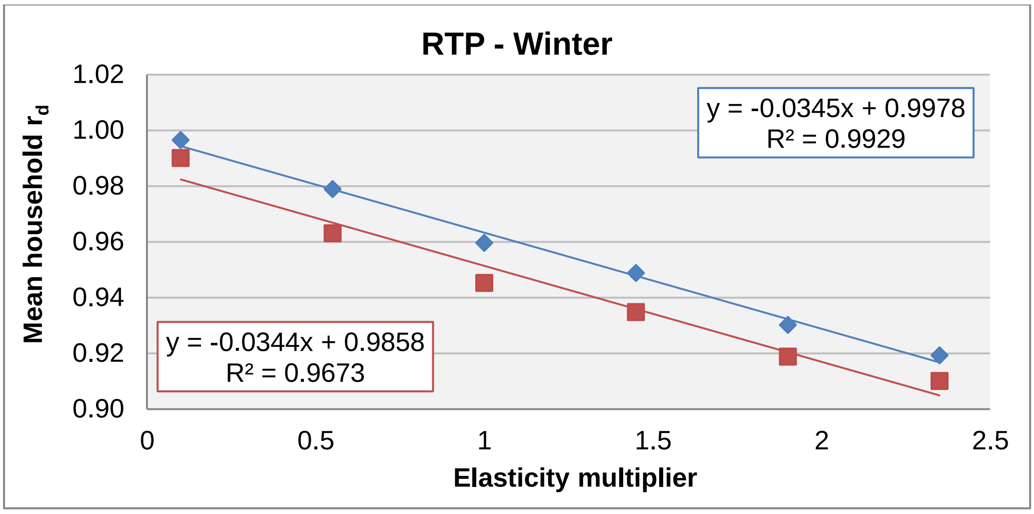

VToU - Autumn
1.02
1.00
0.98
0.96
0.94
0.92
0.90
0.88
Mean household r_d
y = -0.025ln(x) + 0.9388
R² = 0.9822
y = -0.029ln(x) + 0.9241
R² = 0.9797
0
0.5
1
1.5
2
2.5
Elasticity multiplier

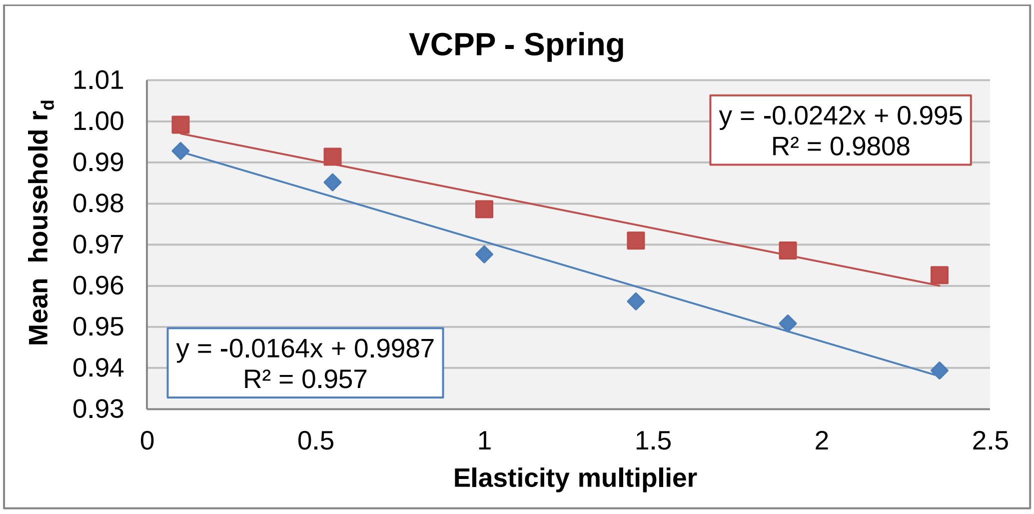

VToU - Winter
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0.90
Mean household r_d
y = -0.013ln(x) + 0.9617
R² = 0.9722
y = -0.023ln(x) + 0.9345
R² = 0.991
0
0.5
1
1.5
2
2.5
Elasticity multiplier

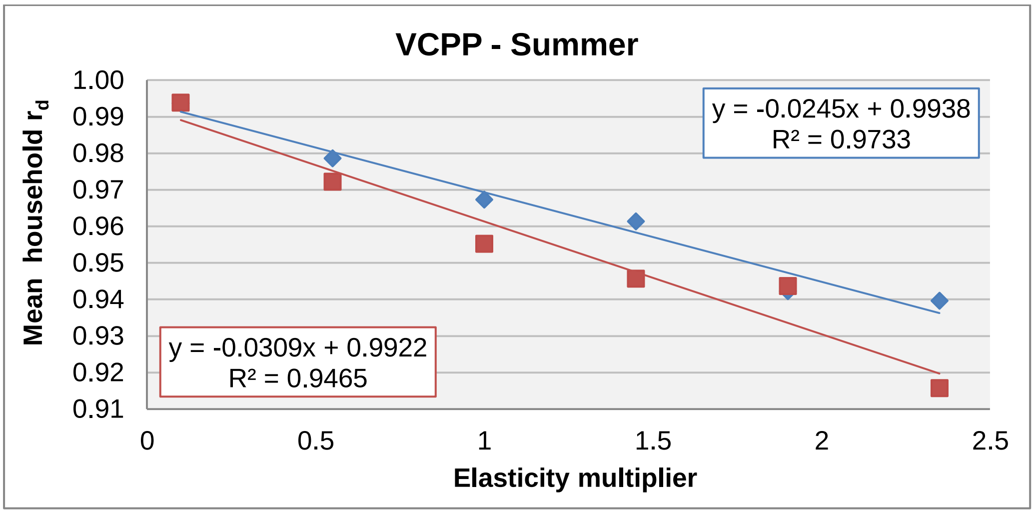

RTP - Spring
Mean household r_d
Elasticity multiplier
y = -0.0255x + 0.9928
R² = 0.9805
y = -0.031ln(x) + 0.9255
R² = 0.9813
1.02
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0
0.5
1
1.5
2
2.5

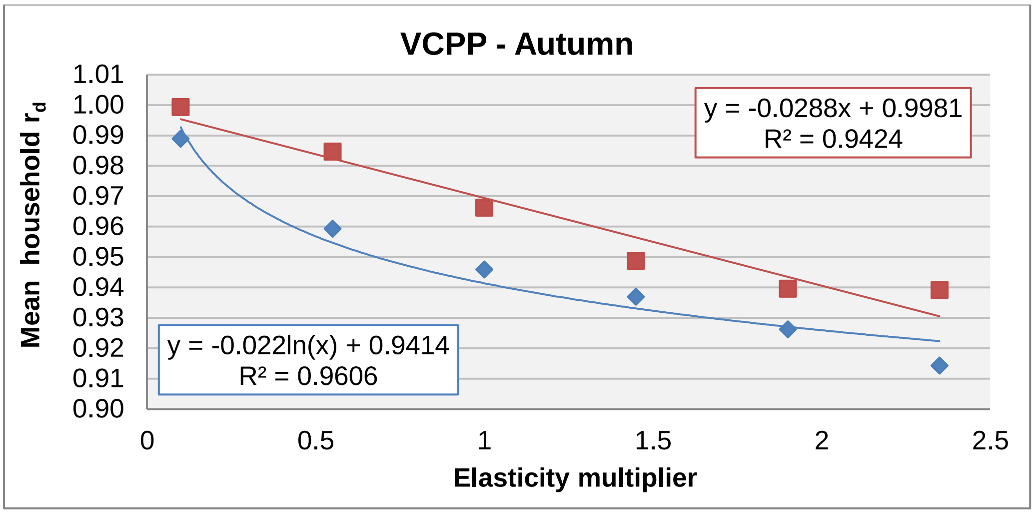

RTP - Summer
Mean household r_d
Elasticity multiplier
y = -0.009ln(x) + 0.9695
R² = 0.9244
y = -0.022ln(x) + 0.9395
R² = 0.9208
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0
0.5
1
1.5
2
2.5

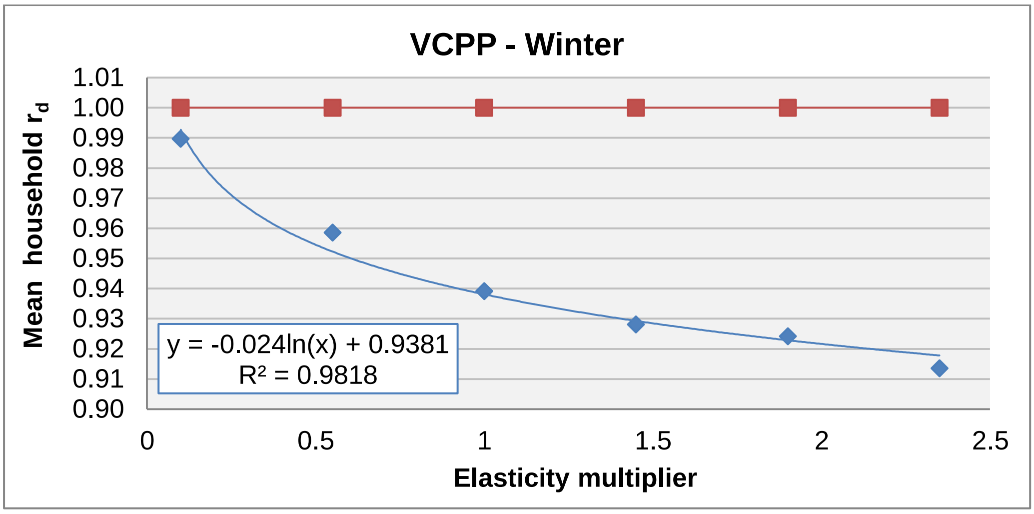

RTP - Autumn
Mean household r_d
Elasticity multiplier
y = -0.017ln(x) + 0.9592
R² = 0.9413
y = -0.022ln(x) + 0.9428
R² = 0.9743
1.01
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0
0.5
1
1.5
2
2.5


RTP - Winter
Mean household r_d
1.02
1.00
0.98
0.96
0.94
0.92
0.90
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = -0.0345x + 0.9978
R² = 0.9929
y = -0.0344 + 0.9858
R² = 0.9673

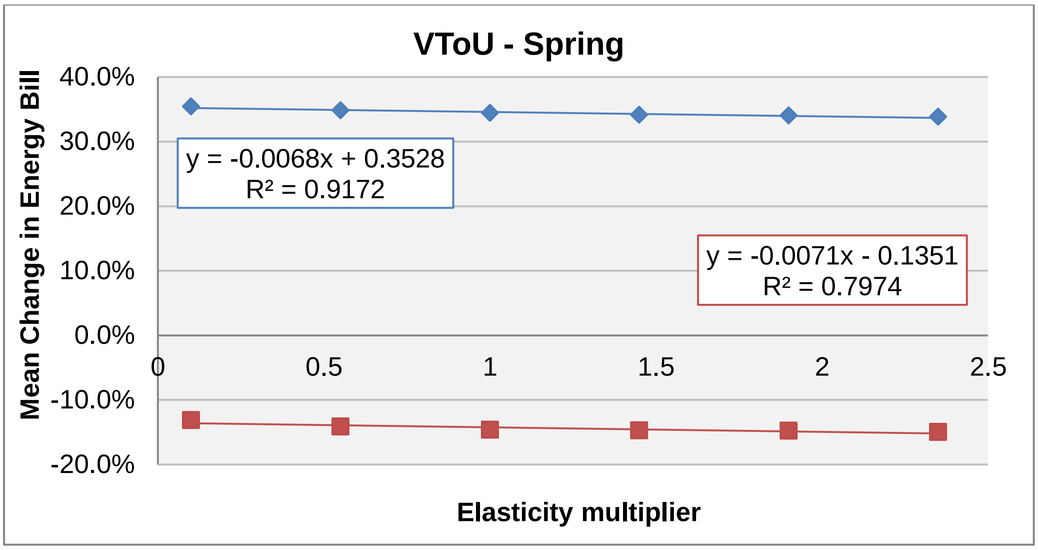

VCPP - Spring
Mean household r_d
1.01
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = -0.0242x + 0.995
R² = 0.9808
y = -0.0164x + 0.9987
R² = 0.957

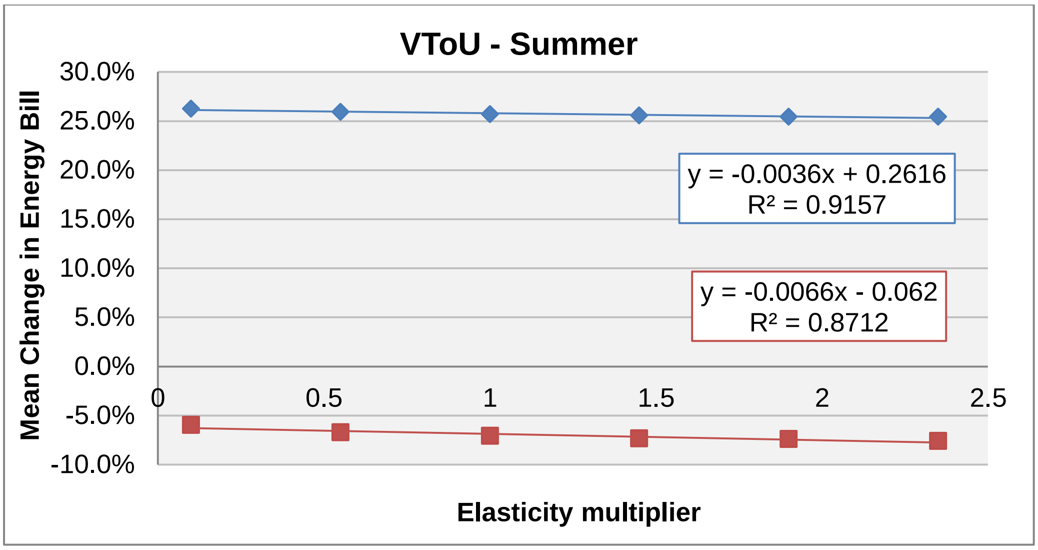

VCPP - Summer
Mean household r_d
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0
0.5
1
1.5
2
2.5
Elasticity multiplier
y = -0.0245x + 0.9938
R² = 0.9733
y = -0.0309x + 0.9922
R² = 0.9465

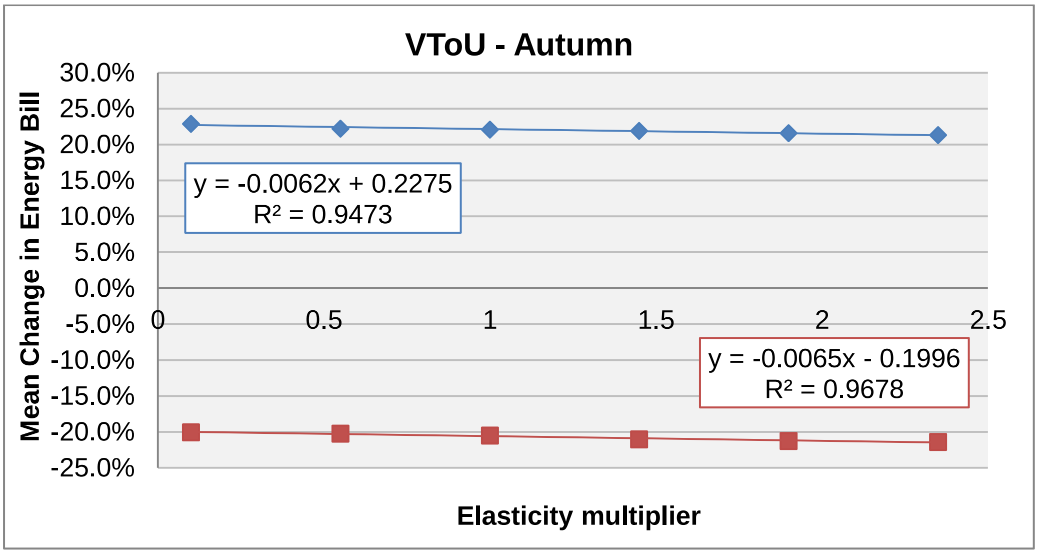


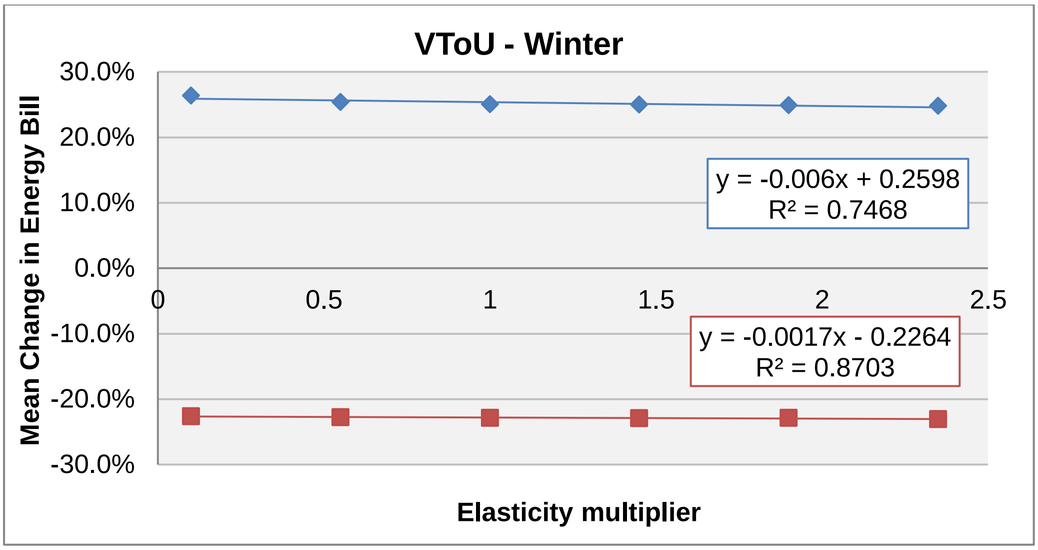


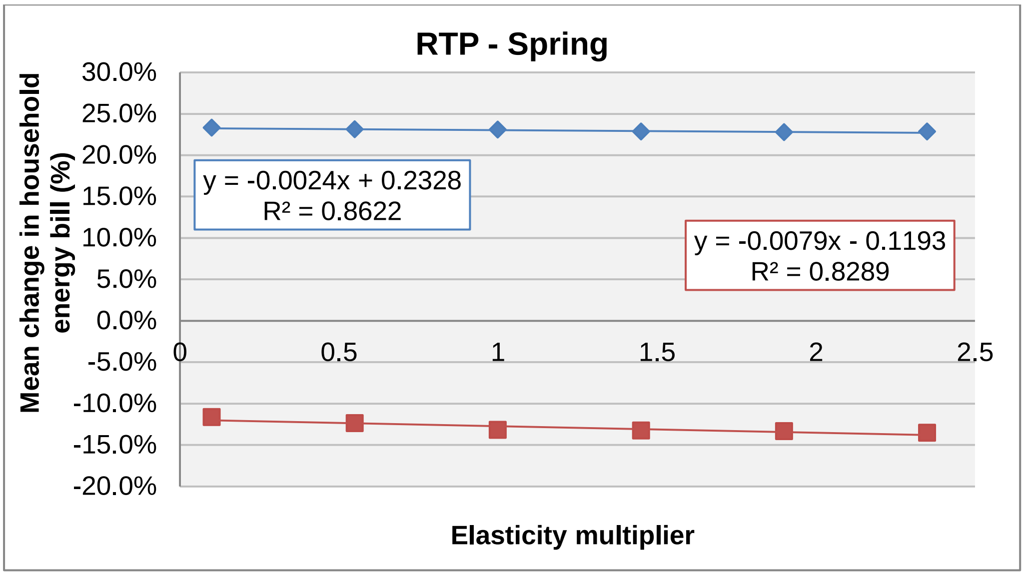
Mean change in daily energy bill:

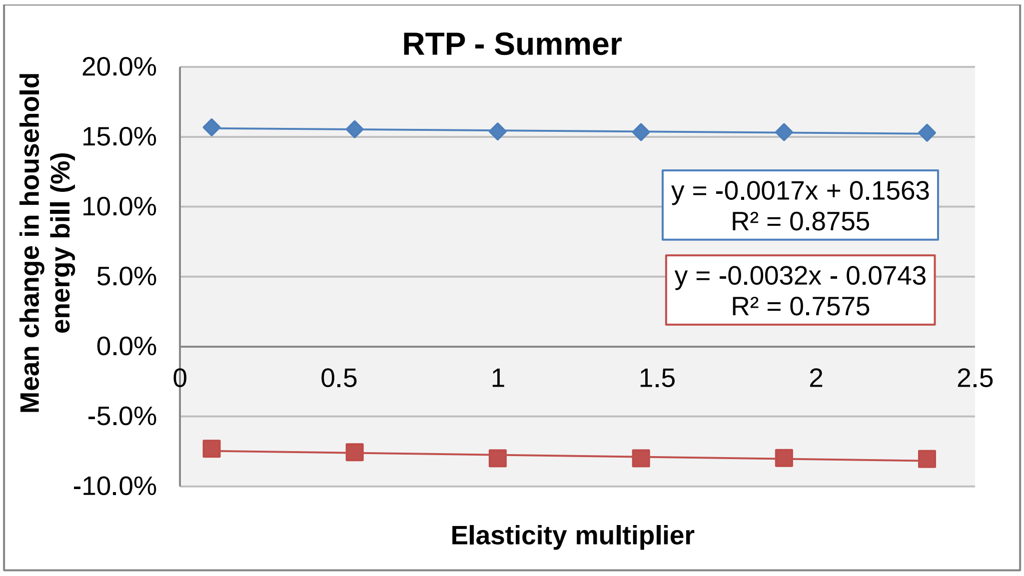

VToU - Spring
Mean Change in Energy Bill
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.0068x + 0.3528
R² = 0.9172
y = -0.0071x - 0.1351
R² = 0.7974
Elasticity multiplier

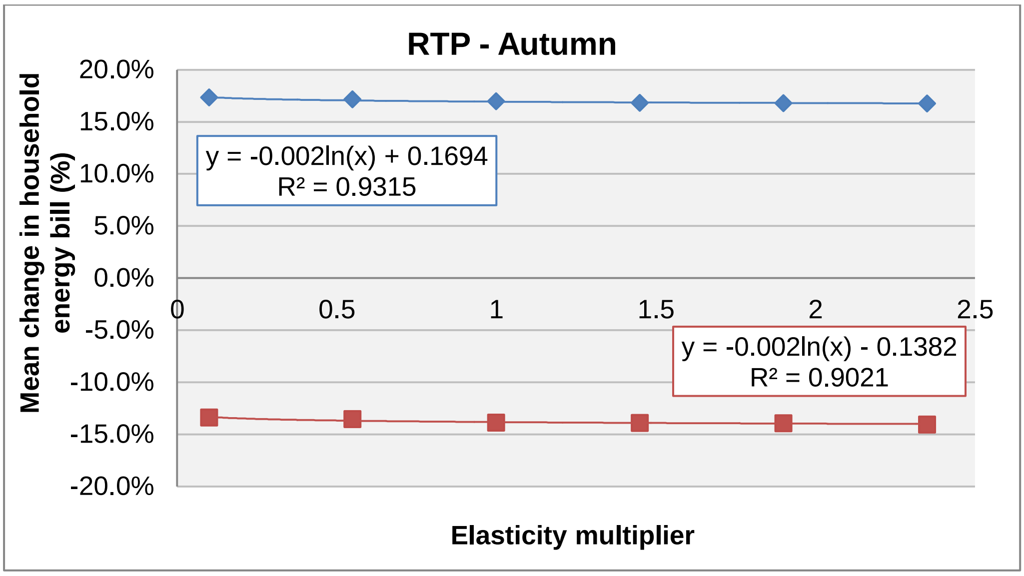

VToU - Summer
Mean Change in Energy Bill
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
0
0.5
1
1.5
2
2.5
y = -0.0036x + 0.2616
R² = 0.9157
y = -0.0066x - 0.062
R² = 0.8712
Elasticity multiplier

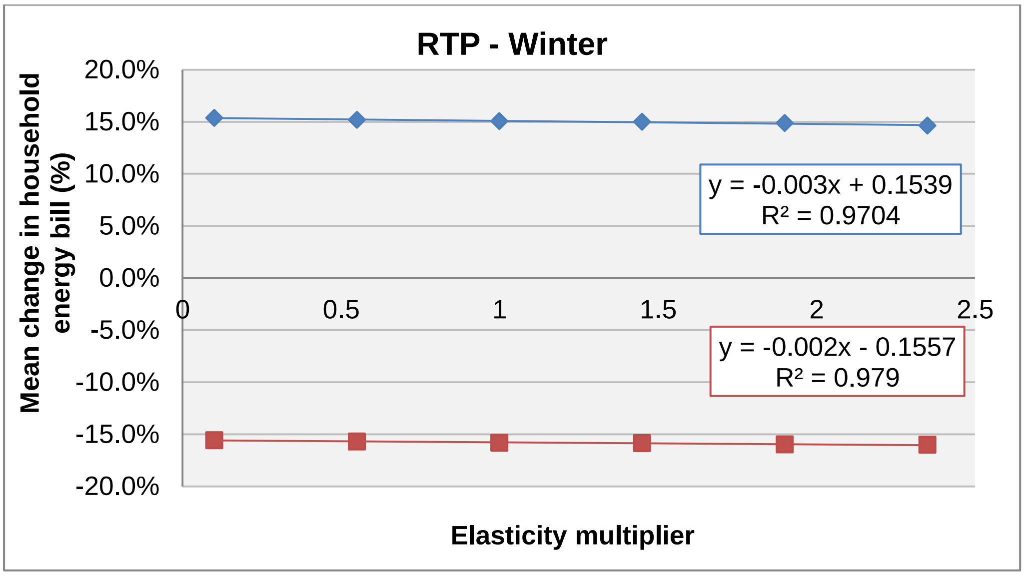

VToU - Autumn
Mean Change in Energy Bill
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
-25.0%
0
0.5
1
1.5
2
2.5
y = -0.0062x + 0.2275
R² = 0.9473
y = -0.0065x - 0.1996
R² = 0.9678
Elasticity multiplier

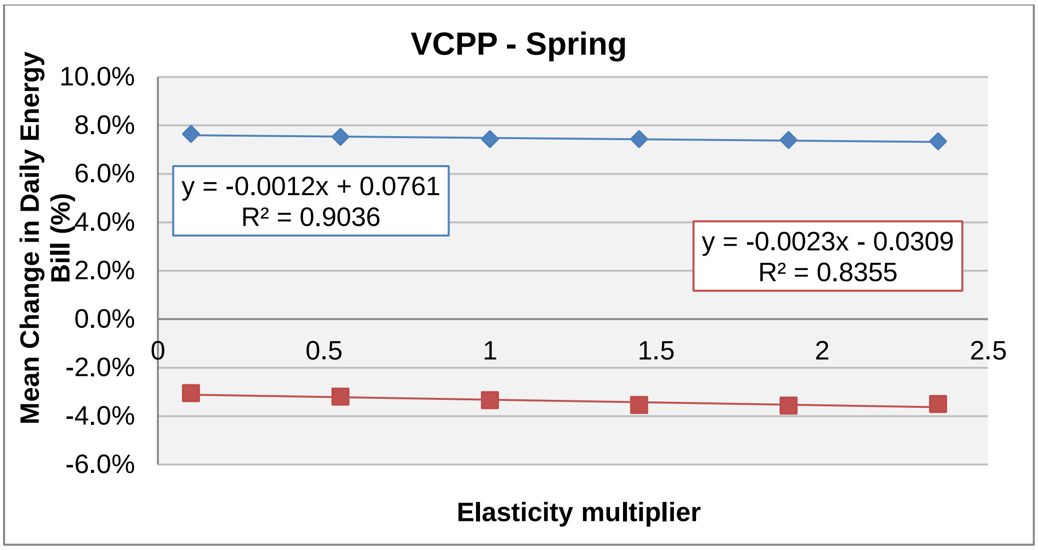

VToU - Winter
Mean Change in Energy Bill
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
-30.0%
0
0.5
1
1.5
2
2.5
y = -0.006x + 0.2598
R² = 0.7468
y = -0.0017x - 0.2264
R² = 0.8703
Elasticity multiplier

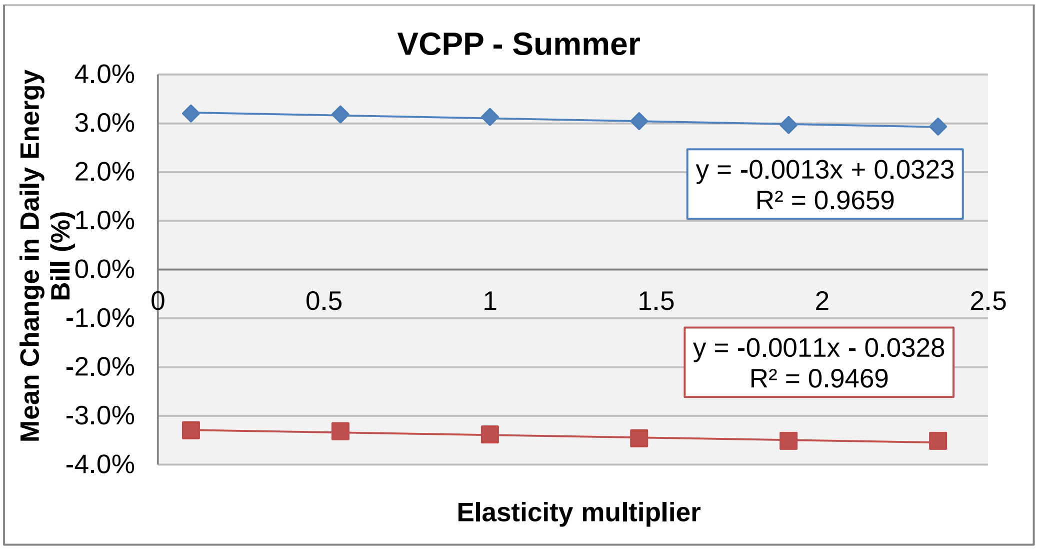

RTP - Spring
Mean change in household energy bill (%)
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.0024x + 0.2328
R² = 0.8622
y = -0.0079x - 0.1193
R² = 0.8289
Elasticity multiplier

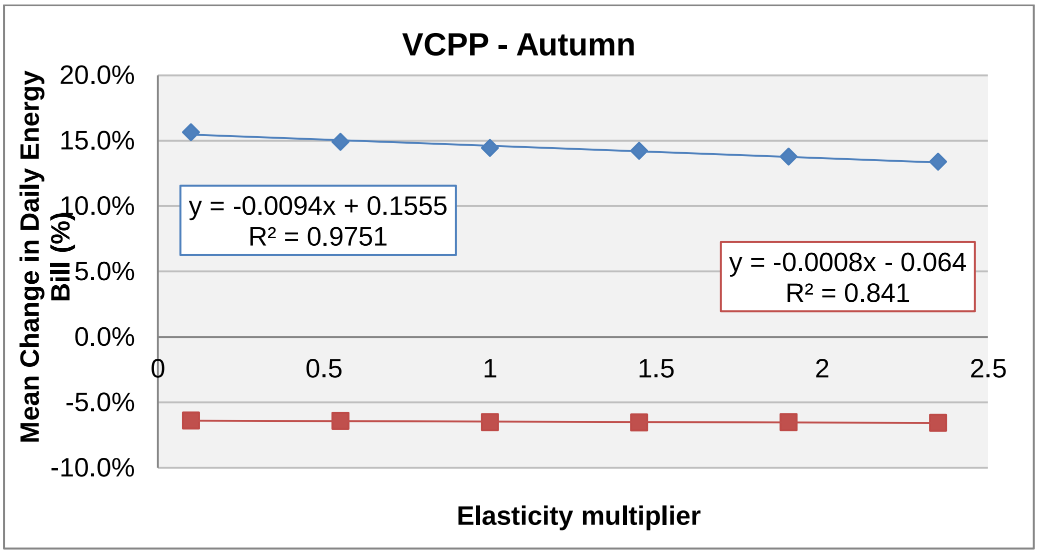

RTP - Summer
Mean change in household energy bill (%)
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
0
0.5
1
1.5
2
2.5
y = -0.0017x + 0.1563
R² = 0.8755
y = -0.0032x - 0.0743
R² = 0.7575
Elasticity multiplier

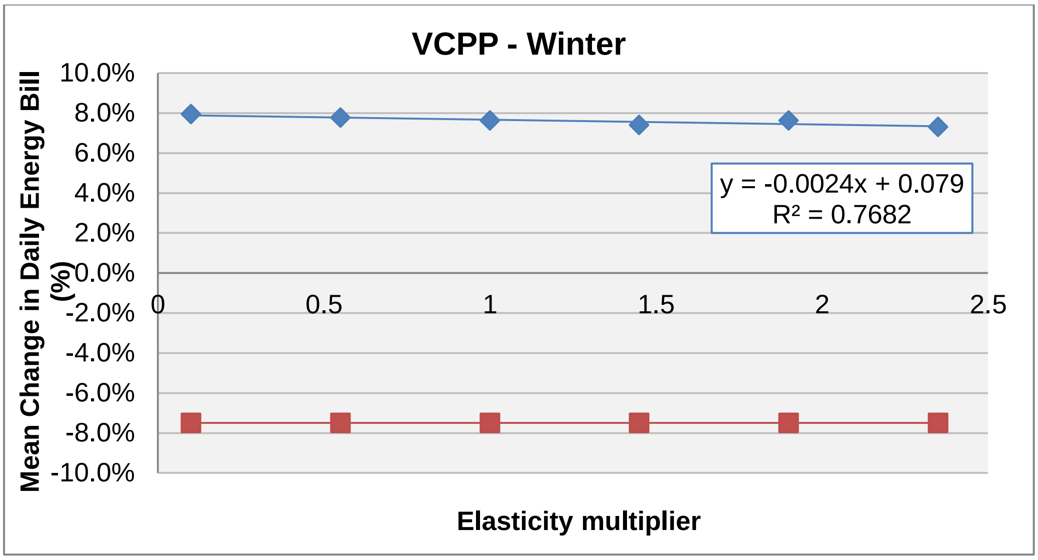

RTP - Autumn
Mean change in household energy bill (%)
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.002ln(x) + 0.1694
R² = 0.9315
y = -0.002ln(x) - 0.1382
R² = 0.9021
Elasticity multiplier


RTP - Winter
Mean change in household energy bill (%)
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
0
0.5
1
1.5
2
2.5
y = -0.003x + 0.1539
R² = 0.9704
y = -0.002x - 0.1557
R² = 0.979
Elasticity multiplier


VCPP - Spring
Mean Change in Daily Energy Bill (%)
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
0
0.5
1
1.5
2
2.5
y = -0.0012x + 0.0761
R² = 0.9036
y = -0.0023x - 0.0309
R² = 0.8355
Elasticity multiplier

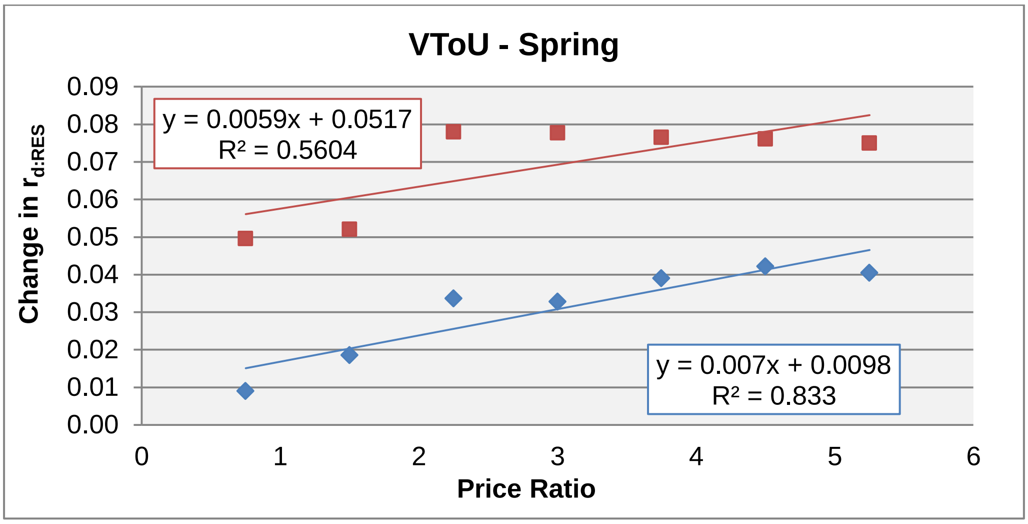

VCPP - Summer
Mean Change in Daily Energy Bill (%)
4.0%
3.0%
2.0%
1.0%
0.0%
-1.0%
-2.0%
-3.0%
-4.0%
0
0.5
1
1.5
2
2.5
y = -0.0013x + 0.0323
R² = 0.9659
y = -0.0011x - 0.0328
R² = 0.9469
Elasticity multiplier

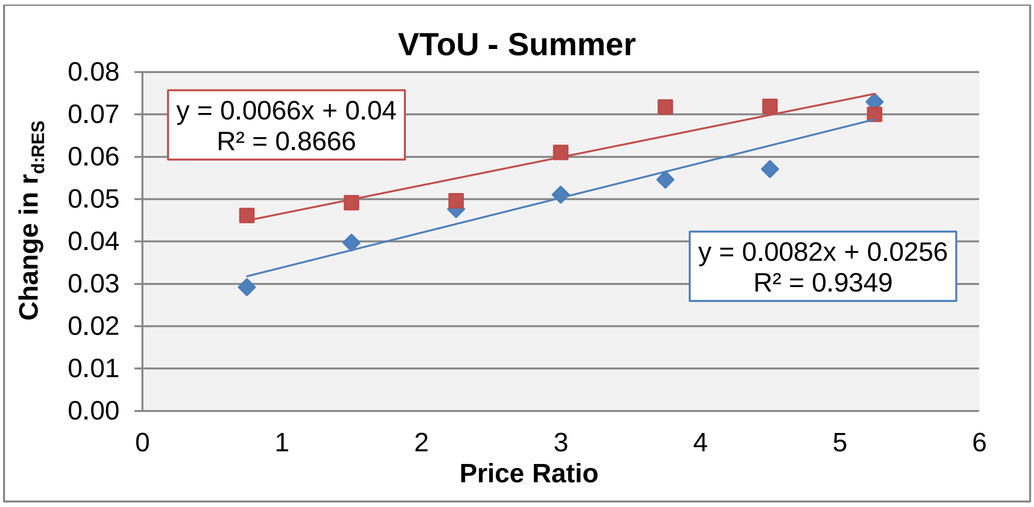

VCPP - Autumn
Mean Change in Daily Energy Bill (%)
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
-10.0%
0
0.5
1
1.5
2
2.5
y = -0.0094x + 0.1555
R² = 0.9751
y = -0.0008x - 0.064
R² = 0.841
Elasticity multiplier

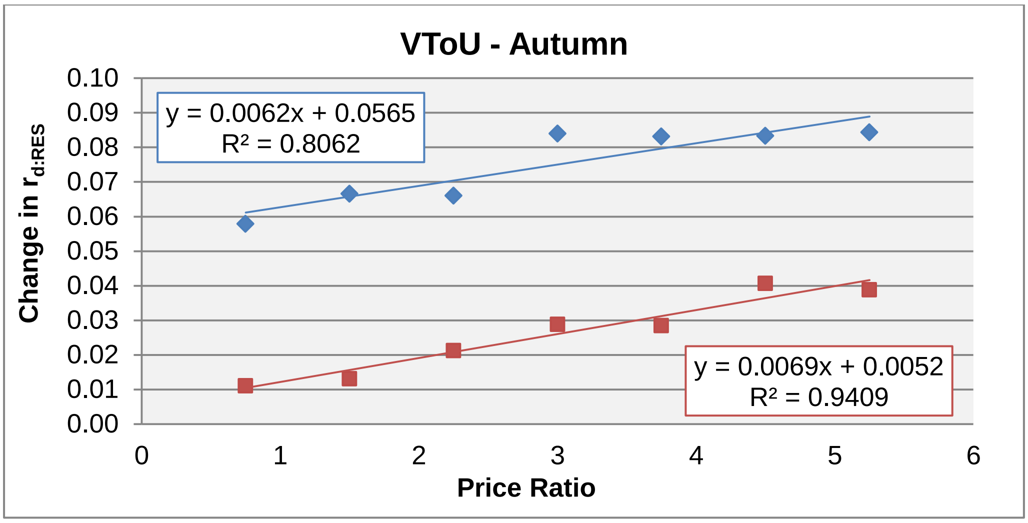


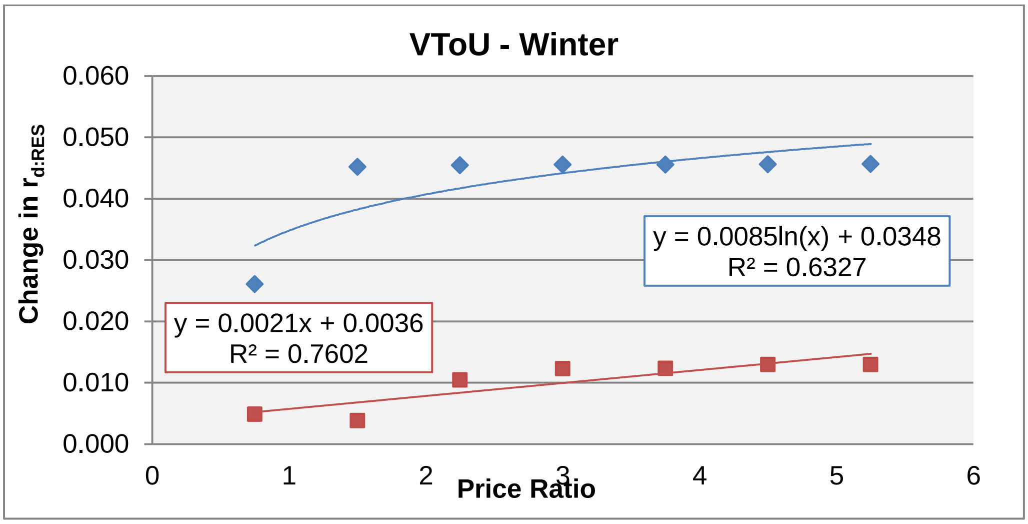
9.2 Sensitivity Analysis 3: Price Ratio

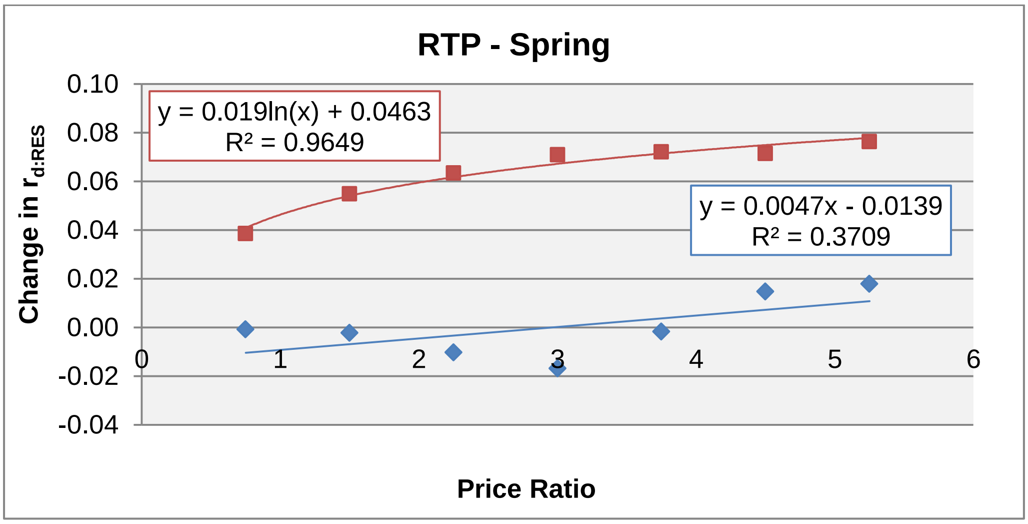
$r_{d:RES}$

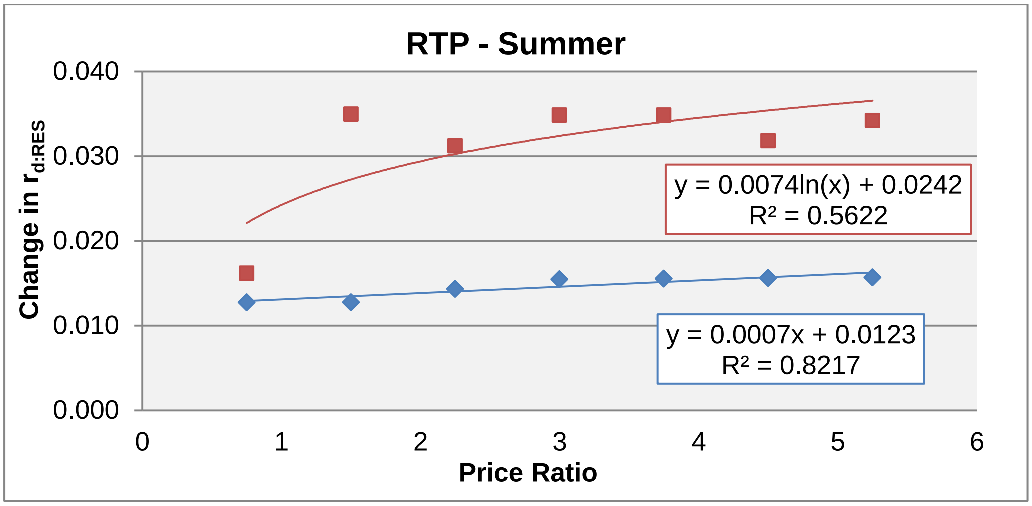


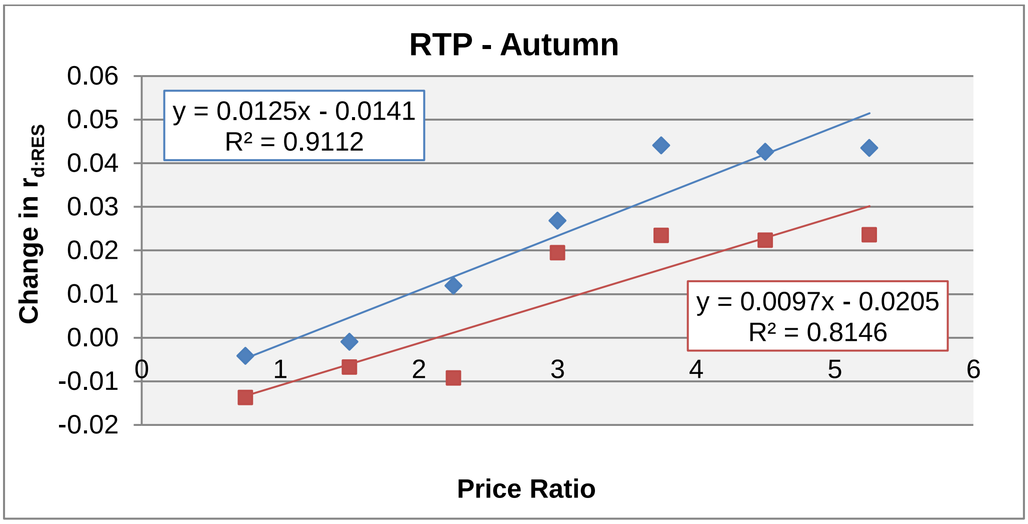


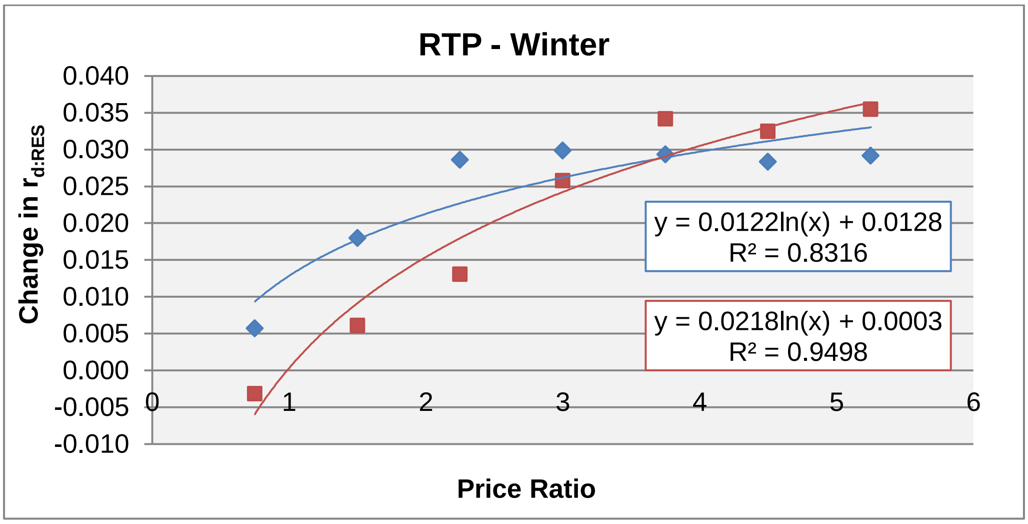

VToU - Autumn
y = 0.0062x + 0.0565
R² = 0.8062
y = 0.0069x + 0.0052
R² = 0.9409
Change in r d:RES
Price Ratio
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
1
2
3
4
5
6

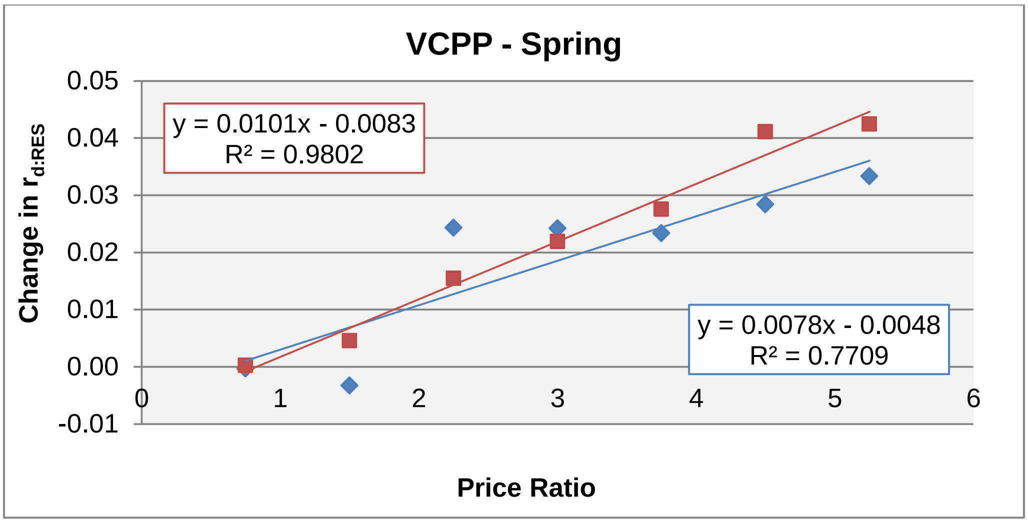

VToU - Winter
y = 0.0085ln(x) + 0.0348
R² = 0.6327
y = 0.0021x + 0.0036
R² = 0.7602
Change in r d:RES
Price Ratio
0.060
0.050
0.040
0.030
0.020
0.010
0.000
0
1
2
3
4
5
6

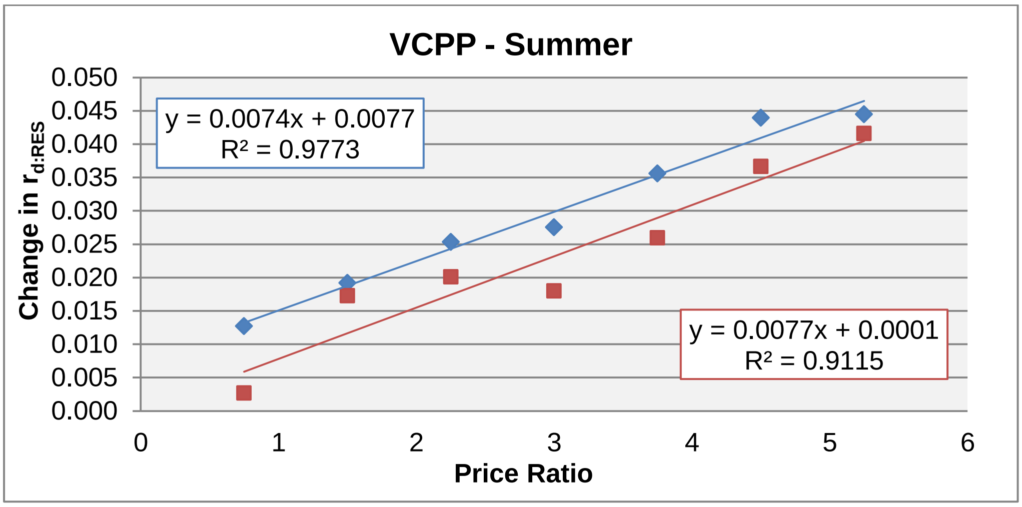

RTP - Spring
y = 0.019ln(x) + 0.0463
R² = 0.9649
y = 0.0047x - 0.0139
R² = 0.3709
Change in r d:RES
Price Ratio
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
0
1
2
3
4
5
6

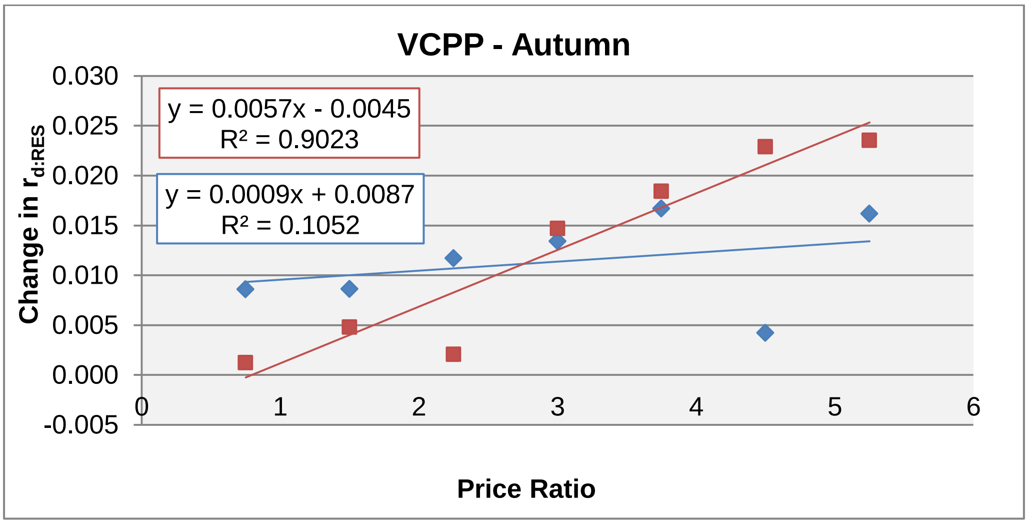

RTP - Summer
Change in $r_{d:RES}$
0.040
0.030
0.020
0.010
0.000
0
1
2
3
4
5
6
Price Ratio
y = 0.0074ln(x) + 0.0242
R² = 0.5622
y = 0.0007x + 0.0123
R² = 0.8217

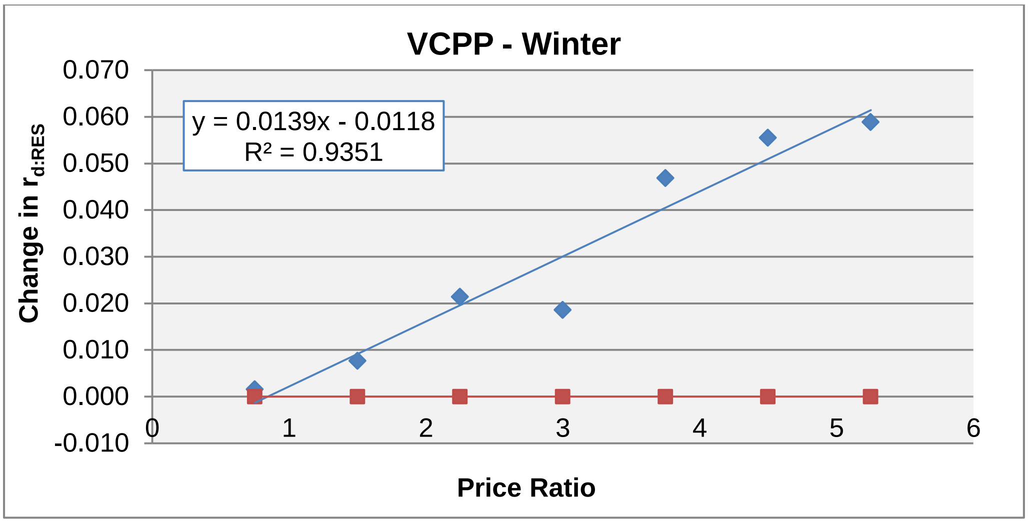

RTP - Autumn
Change in $r_{d:RES}$
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
0
1
2
3
4
5
6
Price Ratio
y = 0.0125x - 0.0141
R² = 0.9112
y = 0.0097x - 0.0205
R² = 0.8146


RTP - Winter
Change in $r_{d:RES}$
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
-0.005
-0.010
0
1
2
3
4
5
6
Price Ratio
y = 0.0122ln(x) + 0.0128
R² = 0.8316
y = 0.0218ln(x) + 0.0003
R² = 0.9498

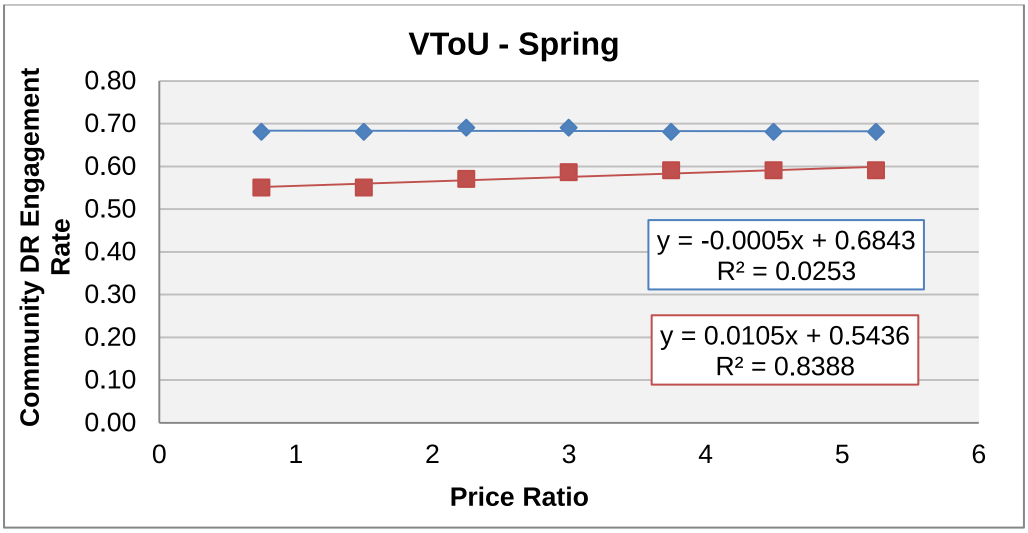

VCPP - Spring
y = 0.0101x - 0.0083
R² = 0.9802
y = 0.0078x - 0.0048
R² = 0.7709
Change in r d:RES
Price Ratio

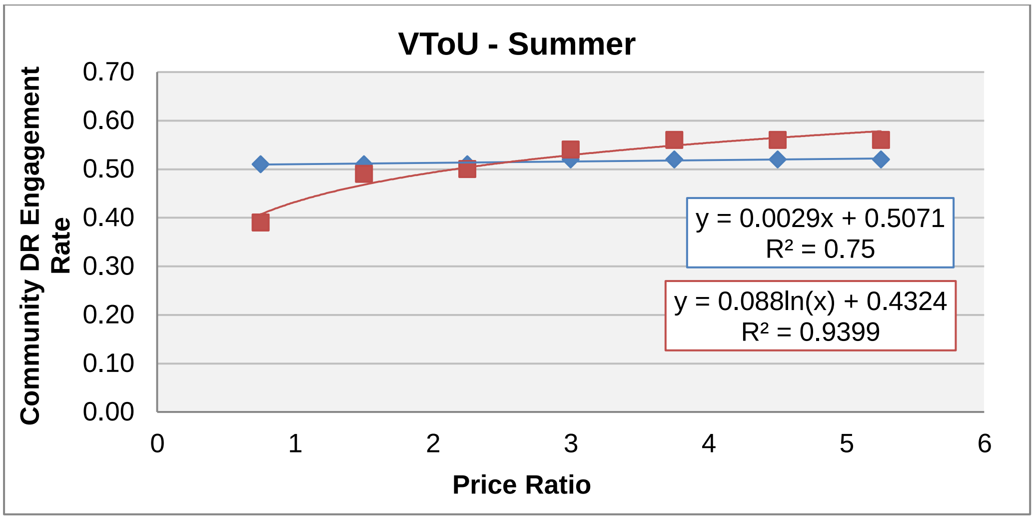

VCPP - Summer
y = 0.0074x + 0.0077
R² = 0.9773
y = 0.0077x + 0.0001
R² = 0.9115
Change in r d:RES
Price Ratio

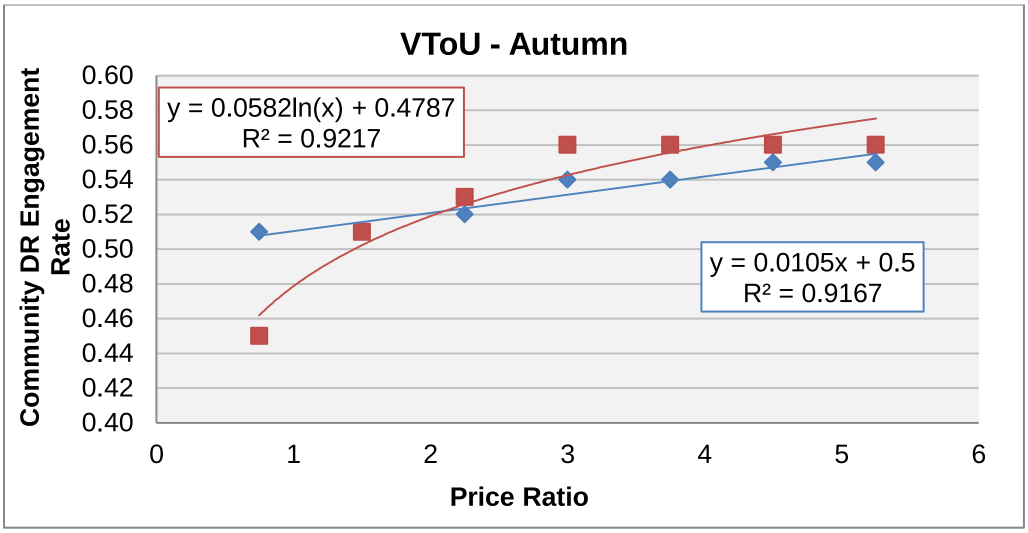

VCPP - Autumn
y = 0.0057x - 0.0045
R² = 0.9023
y = 0.0009x + 0.0087
R² = 0.1052
Change in r d:RES
Price Ratio

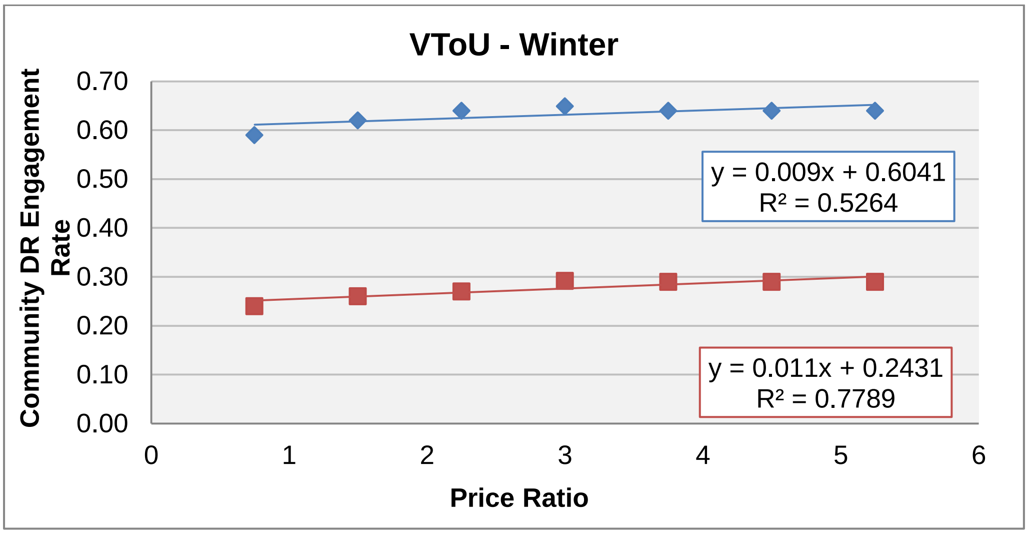


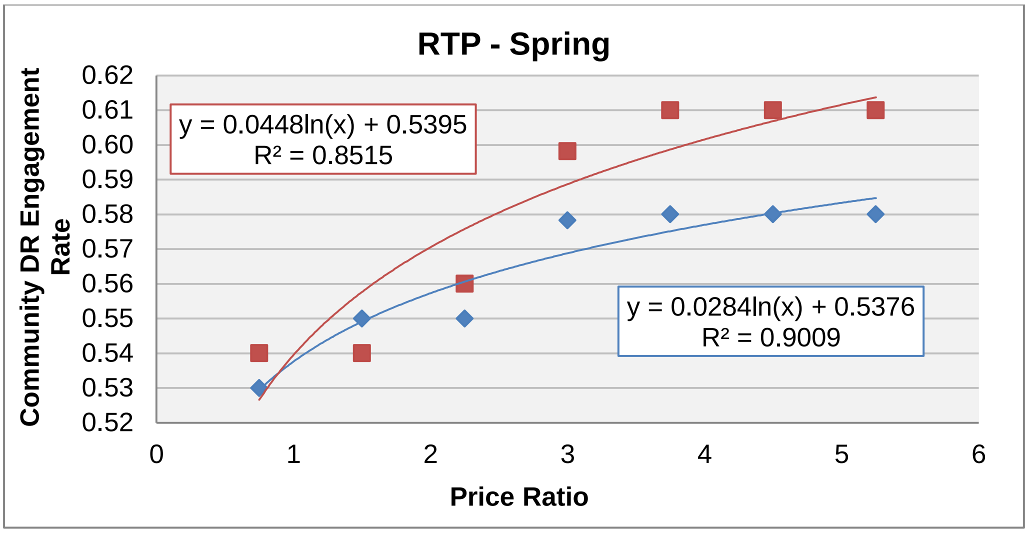
Community Engagement Rate:

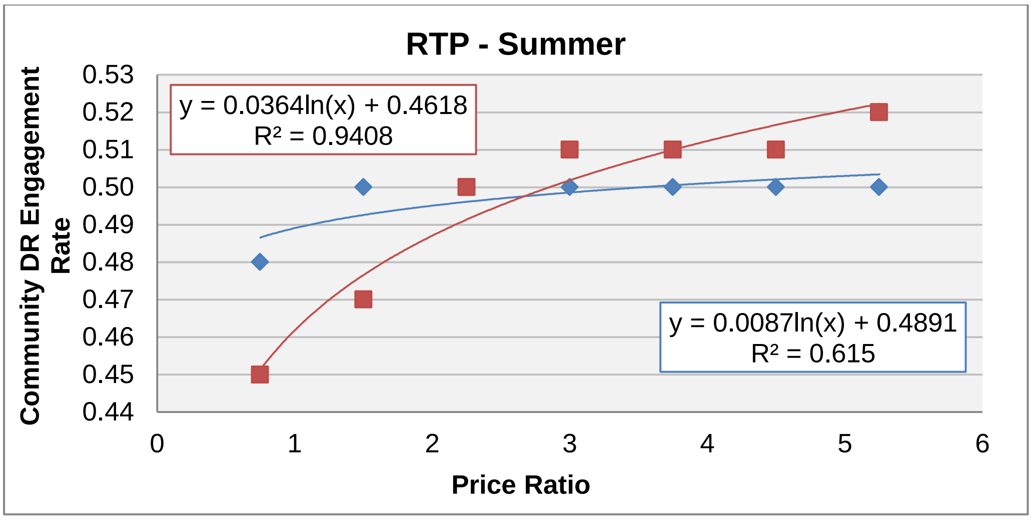


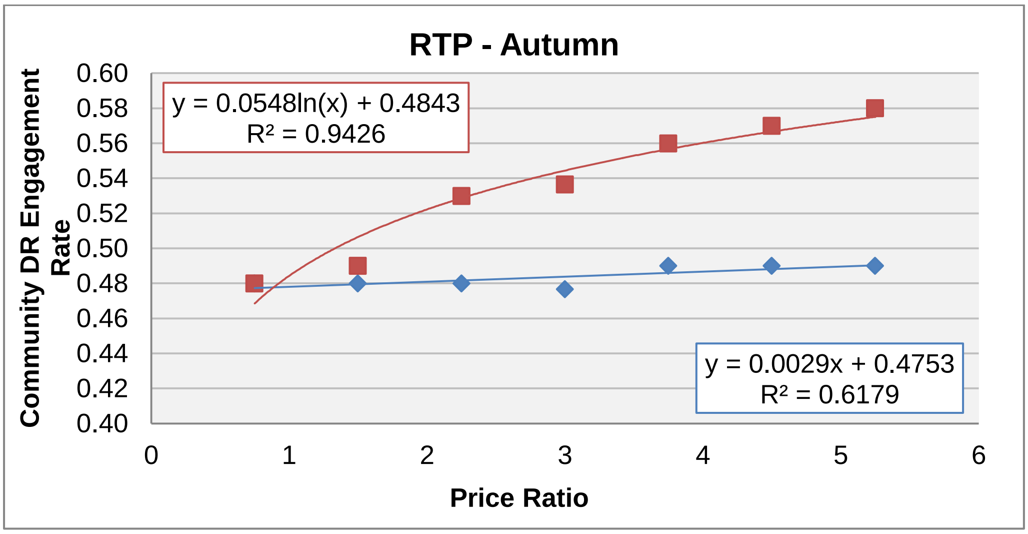

VToU - Summer
Community DR Engagement Rate
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
1
2
3
4
5
6
Price Ratio
y = 0.0029x + 0.5071
R² = 0.75
y = 0.088ln(x) + 0.4324
R² = 0.9399

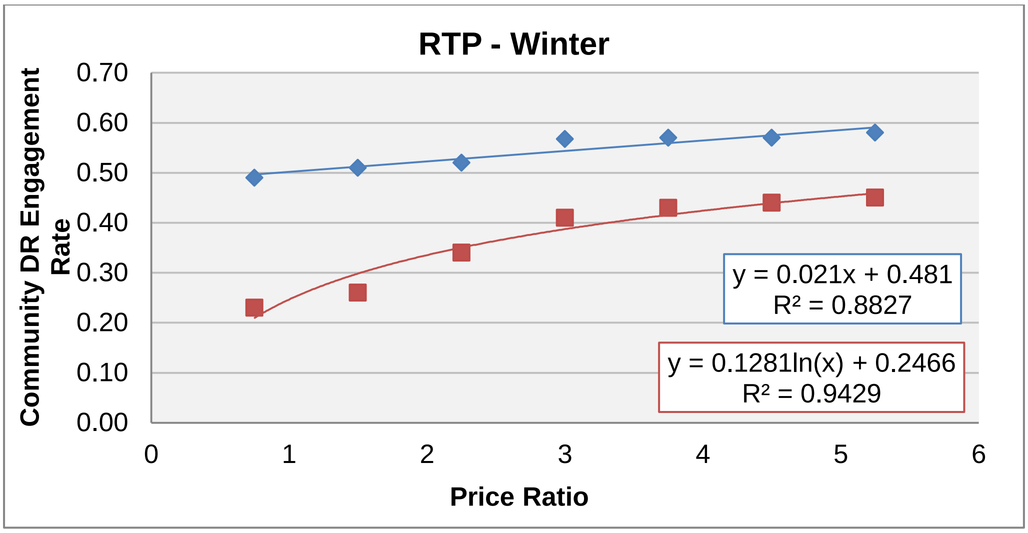

VToU - Autumn
Community DR Engagement Rate
0.60
0.58
0.56
0.54
0.52
0.50
0.48
0.46
0.44
0.42
0.40
0
1
2
3
4
5
6
Price Ratio
y = 0.0582ln(x) + 0.4787
R² = 0.9217
y = 0.0105x + 0.5
R² = 0.9167


VToU - Winter
Community DR Engagement Rate
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
1
2
3
4
5
6
Price Ratio
y = 0.009x + 0.6041
R² = 0.5264
y = 0.011x + 0.2431
R² = 0.7789

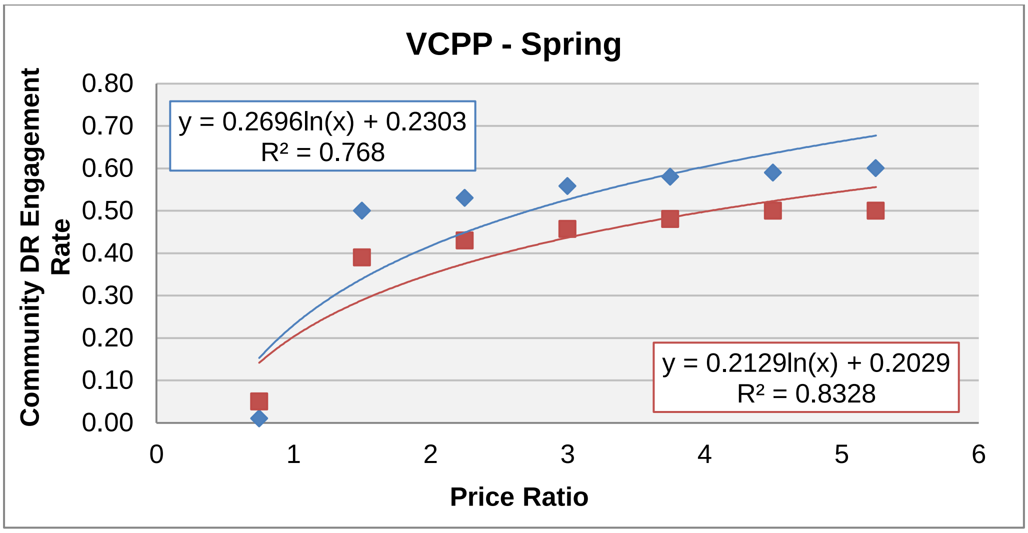

RTP - Spring
y = 0.0448ln(x) + 0.5395
R² = 0.8515
y = 0.0284ln(x) + 0.5376
R² = 0.9009
Community DR Engagement Rate
Price Ratio
0.62
0.61
0.60
0.59
0.58
0.57
0.56
0.55
0.54
0.53
0.52
0
1
2
3
4
5
6


RTP - Summer
y = 0.0364ln(x) + 0.4618
R² = 0.9408
y = 0.0087ln(x) + 0.4891
R² = 0.615
Community DR Engagement Rate
Price Ratio
0.53
0.52
0.51
0.50
0.49
0.48
0.47
0.46
0.45
0.44
0
1
2
3
4
5
6

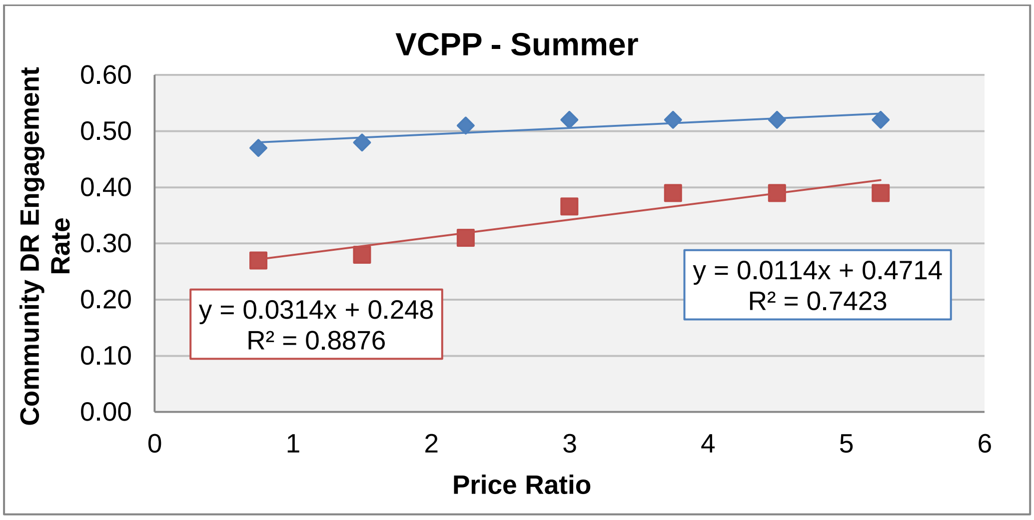

RTP - Autumn
y = 0.0548ln(x) + 0.4843
R² = 0.9426
y = 0.0029x + 0.4753
R² = 0.6179
Community DR Engagement Rate
Price Ratio
0.60
0.58
0.56
0.54
0.52
0.50
0.48
0.46
0.44
0.42
0.40
0
1
2
3
4
5
6



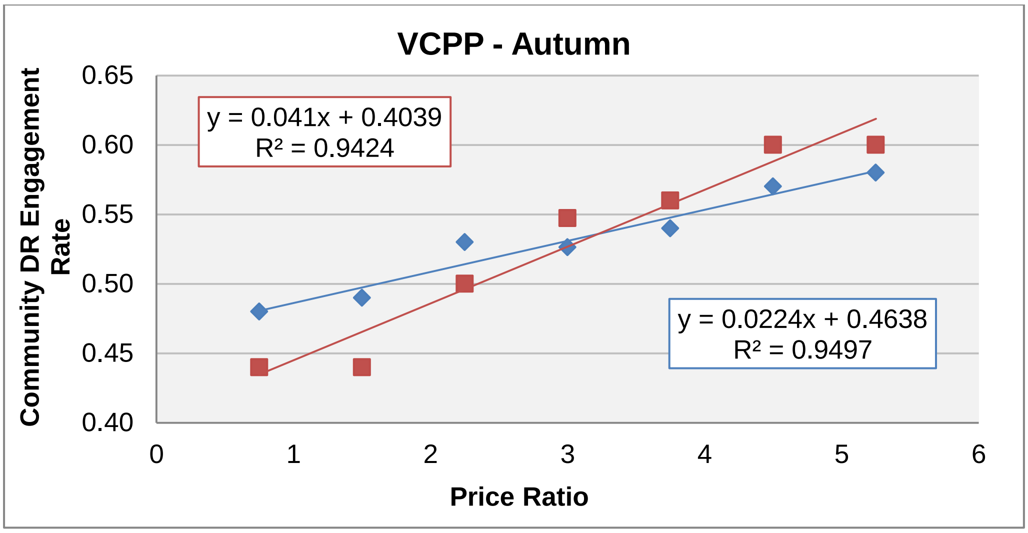
RTP - Winter
Community DR Engagement Rate
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
1
2
3
4
5
6
Price Ratio
y = 0.021x + 0.481
R² = 0.8827
y = 0.1281ln(x) + 0.2466
R² = 0.9429

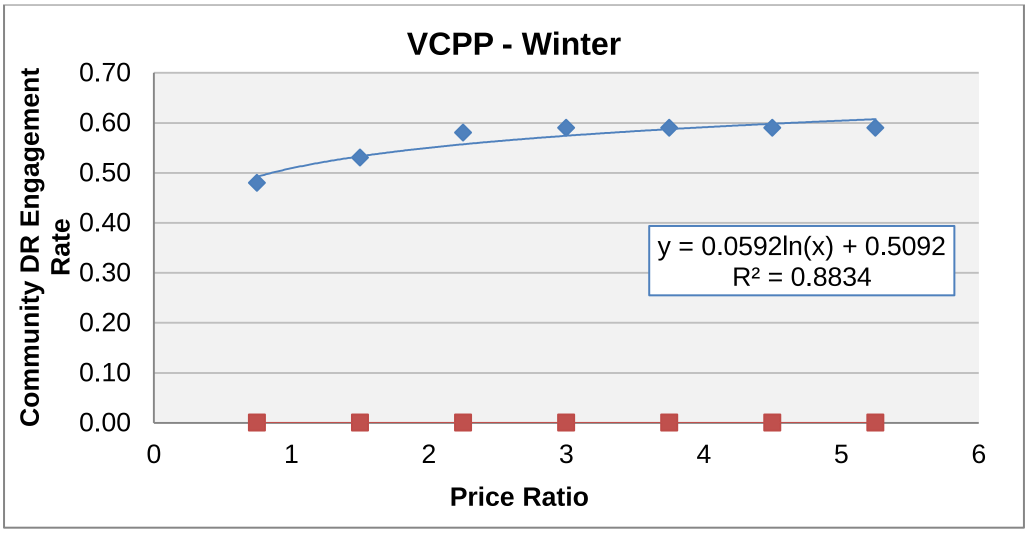


VCPP - Spring
Community DR Engagement Rate
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
1
2
3
4
5
6
Price Ratio
y = 0.2696ln(x) + 0.2303
R² = 0.768
y = 0.2129ln(x) + 0.2029
R² = 0.8328

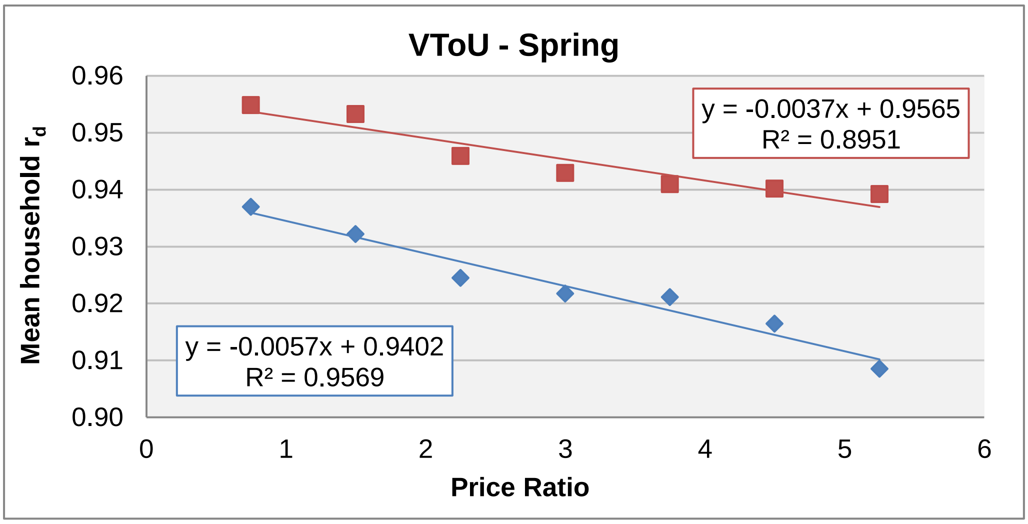


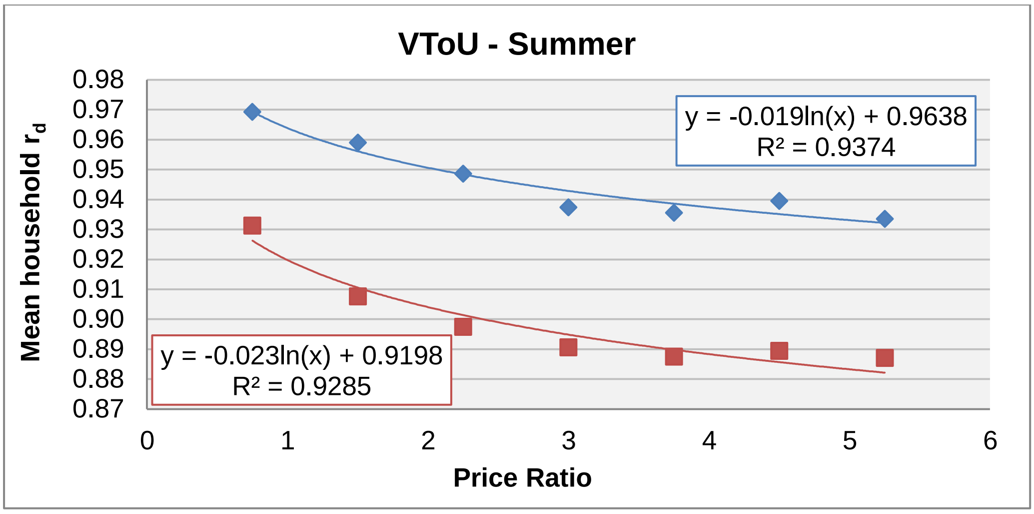
VCPP - Summer
Community DR Engagement Rate
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
1
2
3
4
5
6
Price Ratio
y = 0.0114x + 0.4714
R² = 0.7423
y = 0.0314x + 0.248
R² = 0.8876

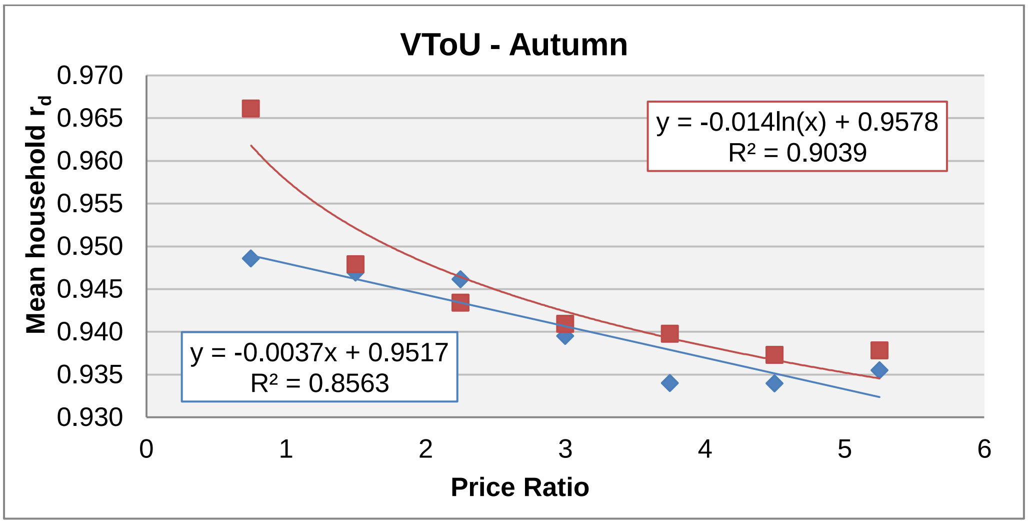


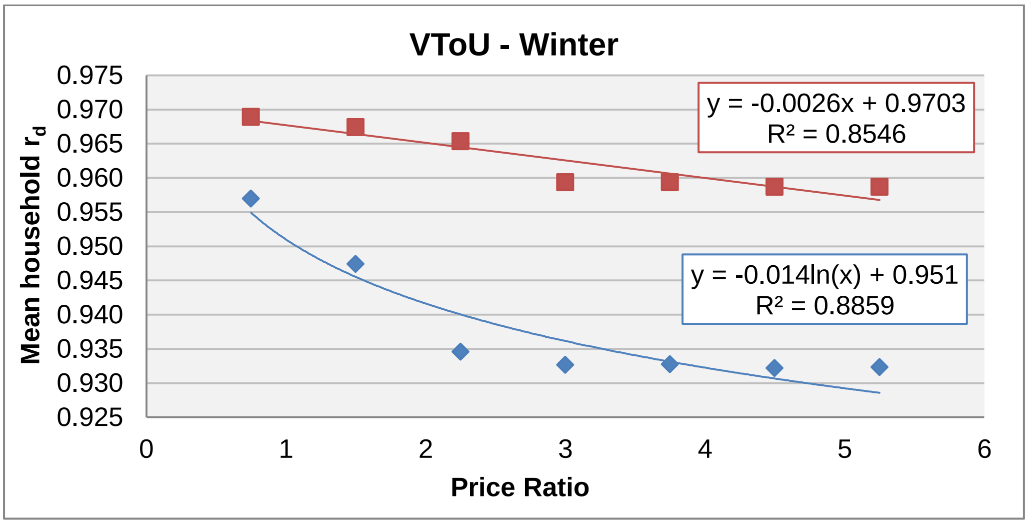


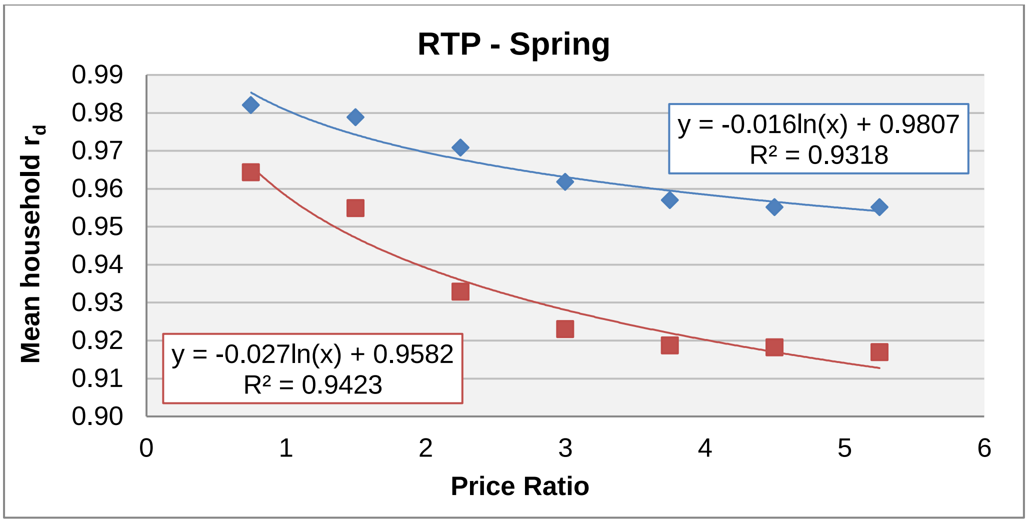
Mean household r_d:

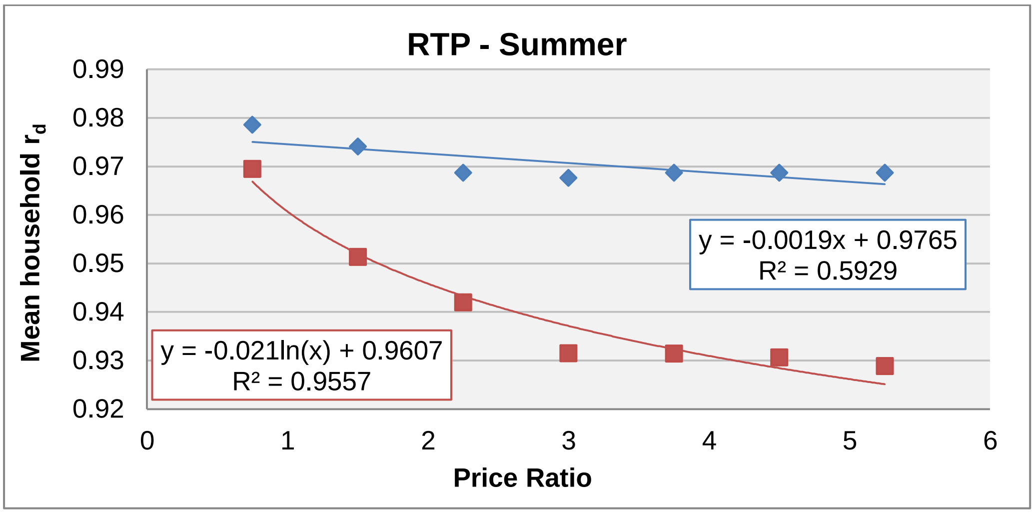


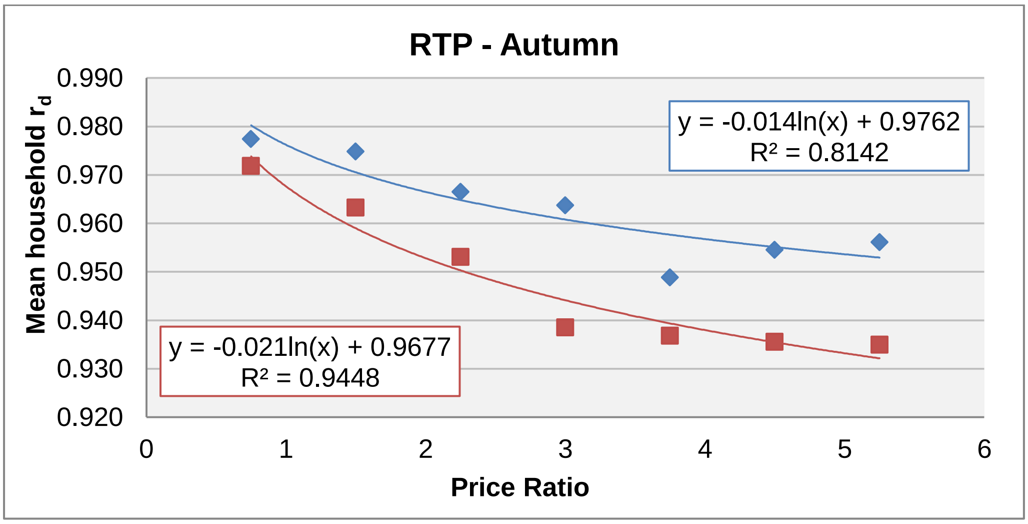

VToU - Summer
Mean household r_d
Price Ratio
y = -0.019ln(x) + 0.9638
R² = 0.9374
y = -0.023ln(x) + 0.9198
R² = 0.9285

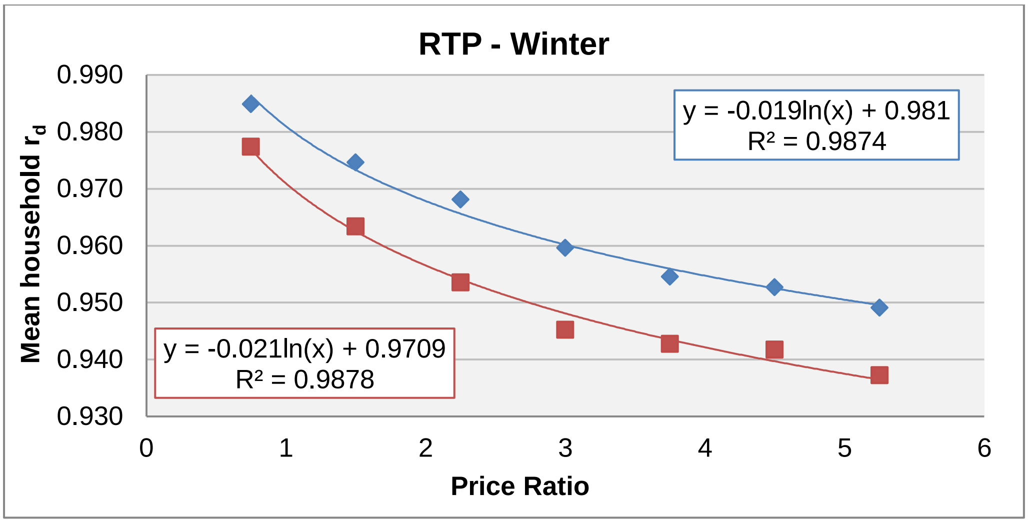

VToU - Autumn
Mean household r_d
Price Ratio
y = -0.014ln(x) + 0.9578
R² = 0.9039
y = -0.0037x + 0.9517
R² = 0.8563

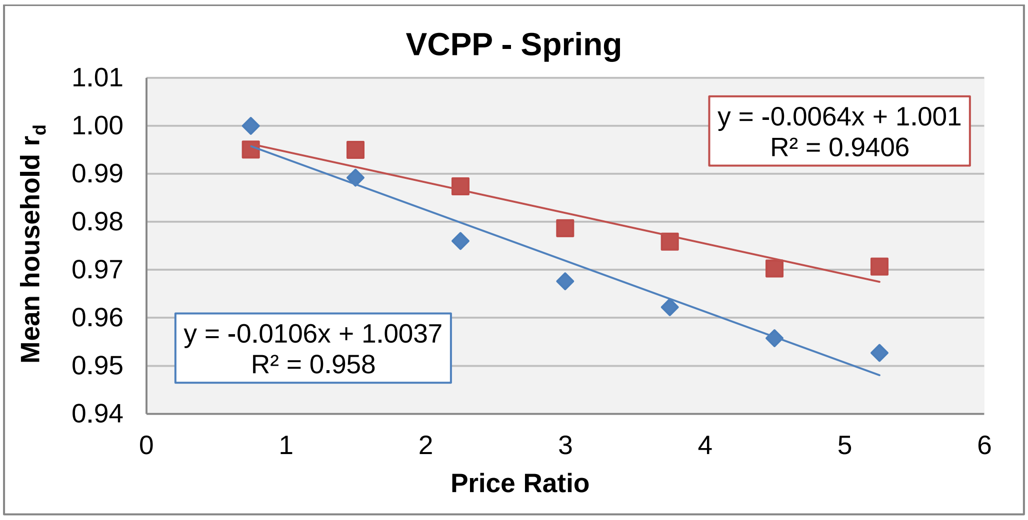

VToU - Winter
Mean household r_d
Price Ratio
y = -0.0026x + 0.9703
R² = 0.8546
y = -0.014ln(x) + 0.951
R² = 0.8859

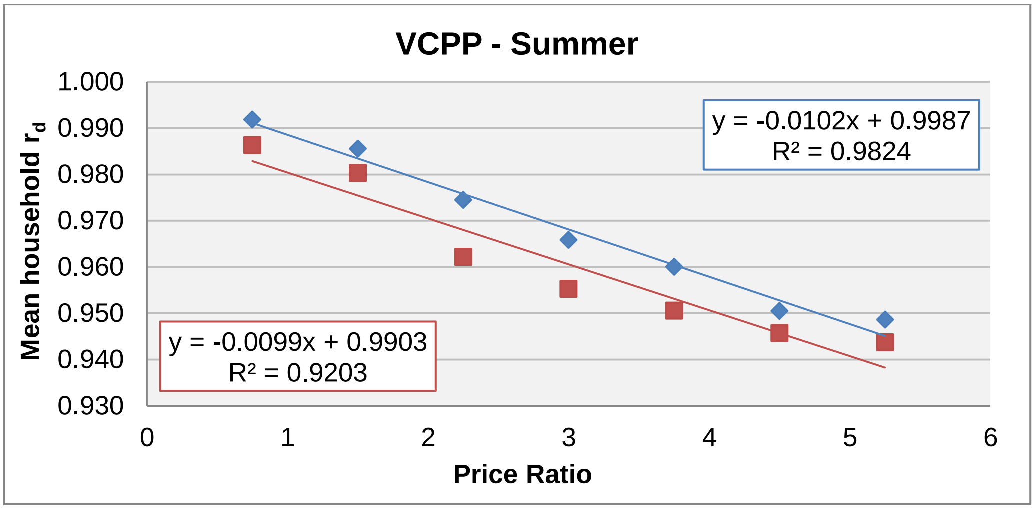

RTP - Spring
Mean household r_d
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
0.90
0
1
2
3
4
5
6
Price Ratio
y = -0.016ln(x) + 0.9807
R² = 0.9318
y = -0.027ln(x) + 0.9582
R² = 0.9423

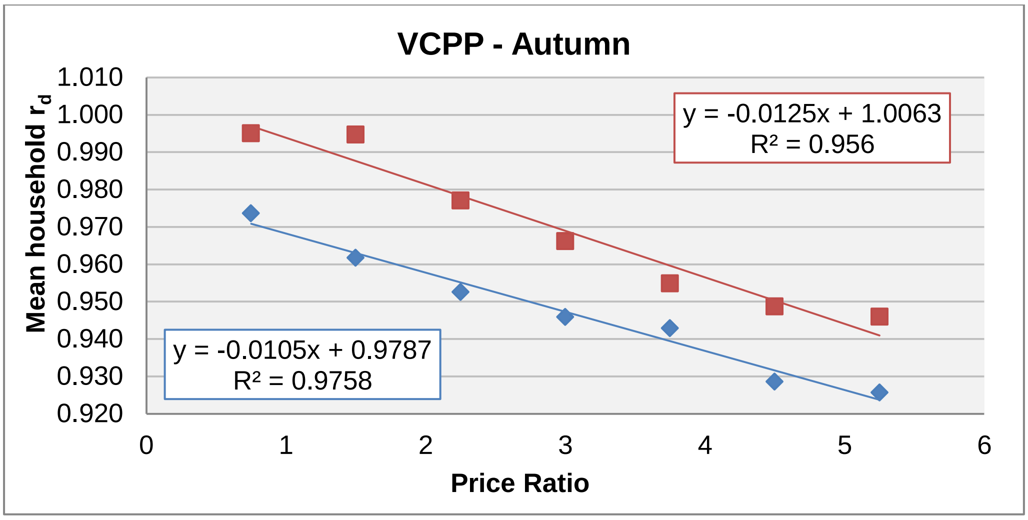

RTP - Summer
Mean household r_d
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0
1
2
3
4
5
6
Price Ratio
y = -0.0019x + 0.9765
R² = 0.5929
y = -0.021ln(x) + 0.9607
R² = 0.9557

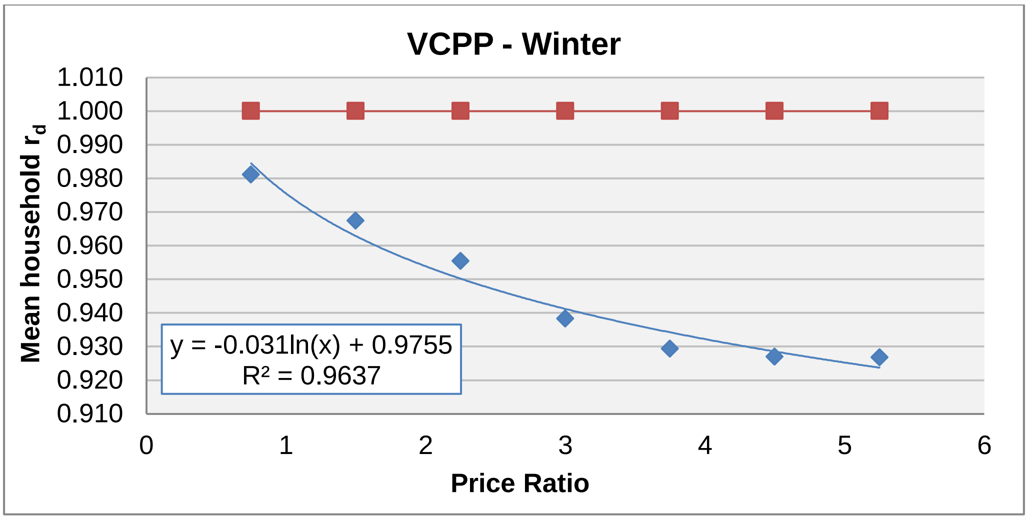

RTP - Autumn
Mean household r_d
0.990
0.980
0.970
0.960
0.950
0.940
0.930
0.920
0
1
2
3
4
5
6
Price Ratio
y = -0.014ln(x) + 0.9762
R² = 0.8142
y = -0.021ln(x) + 0.9677
R² = 0.9448


RTP - Winter
y = -0.019ln(x) + 0.981
R² = 0.9874
y = -0.021ln(x) + 0.9709
R² = 0.9878
Mean household rd
Price Ratio

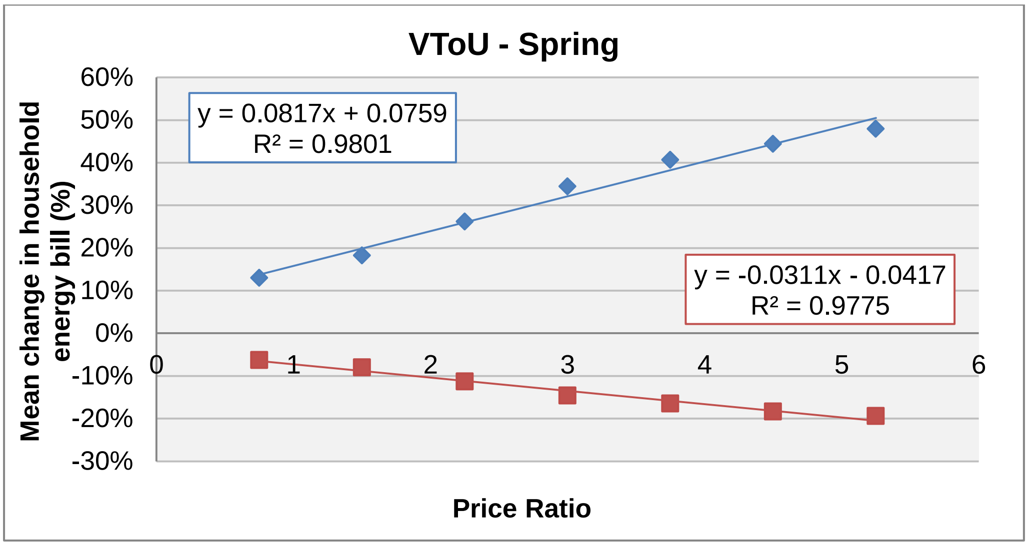

VCPP - Spring
y = -0.0064x + 1.001
R² = 0.9406
y = -0.0106x + 1.0037
R² = 0.958
Mean household rd
Price Ratio

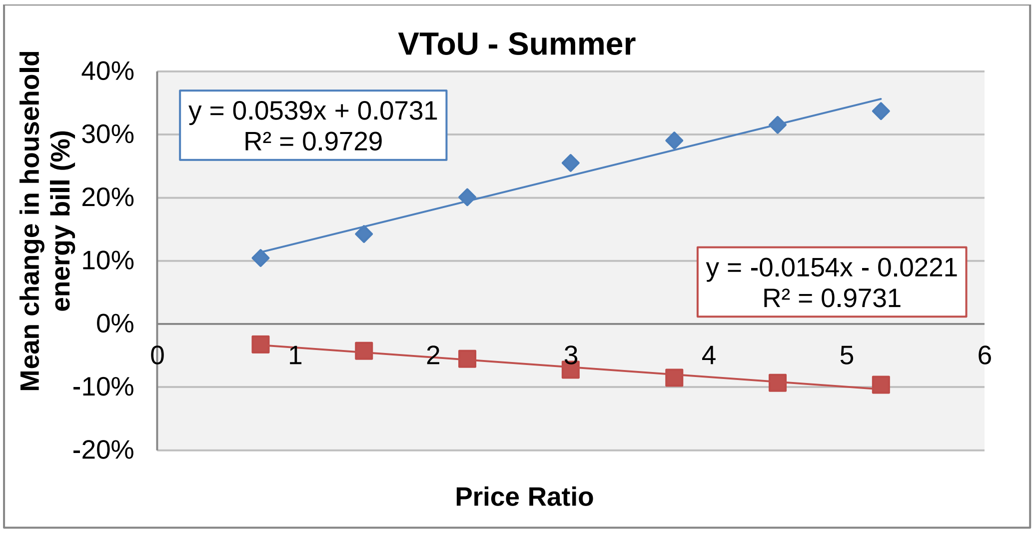

VCPP - Summer
y = -0.0102x + 0.9987
R² = 0.9824
y = -0.0099x + 0.9903
R² = 0.9203
Mean household rd
Price Ratio

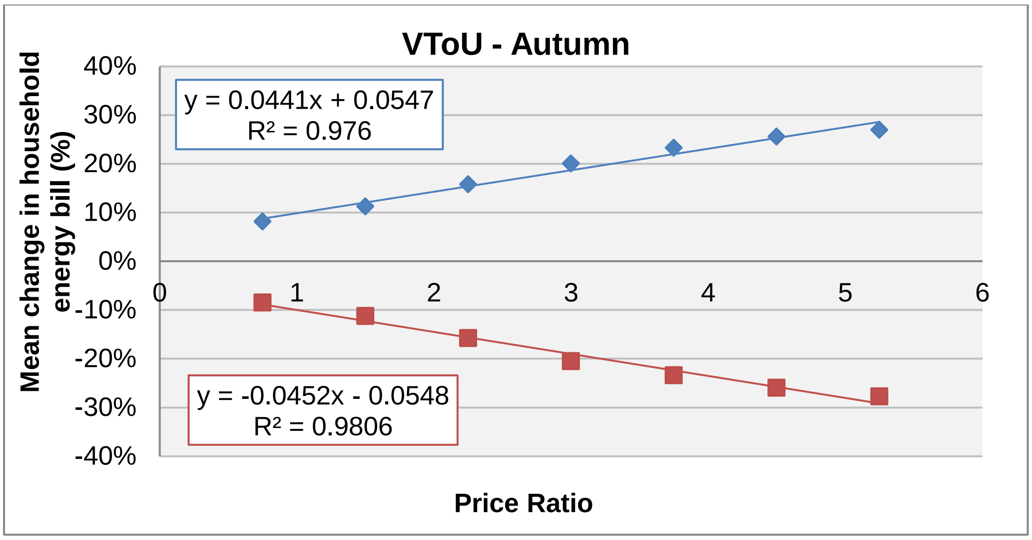


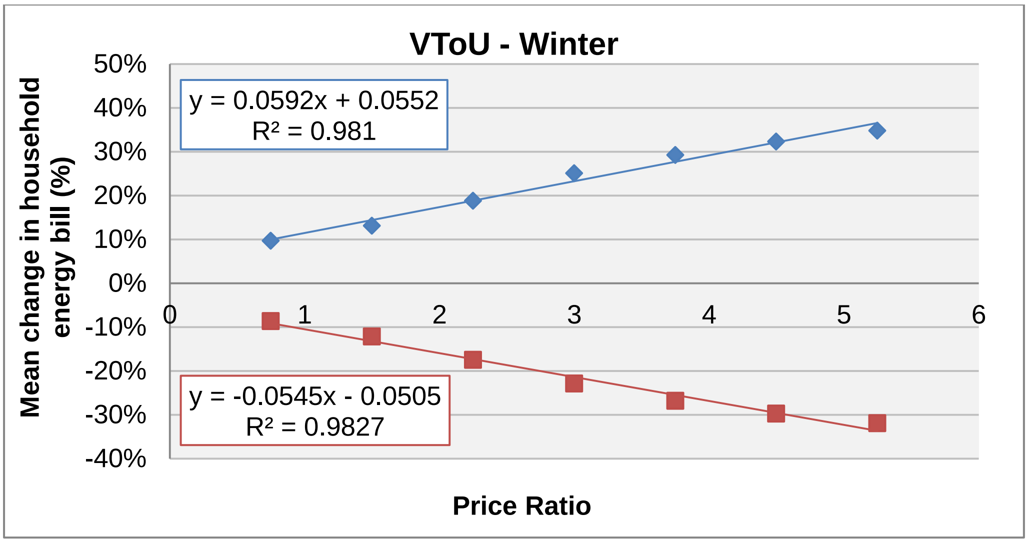


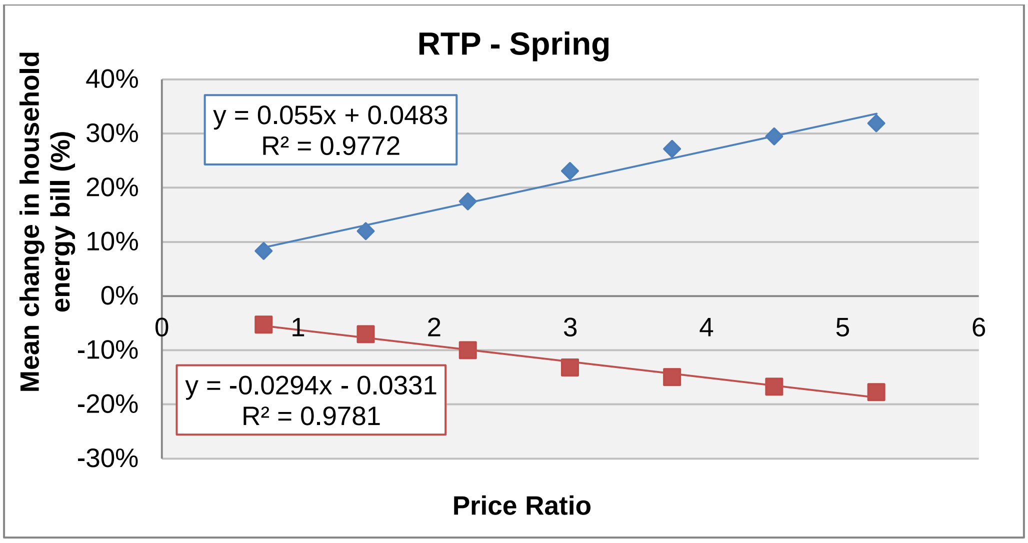
Mean change in daily energy bill:

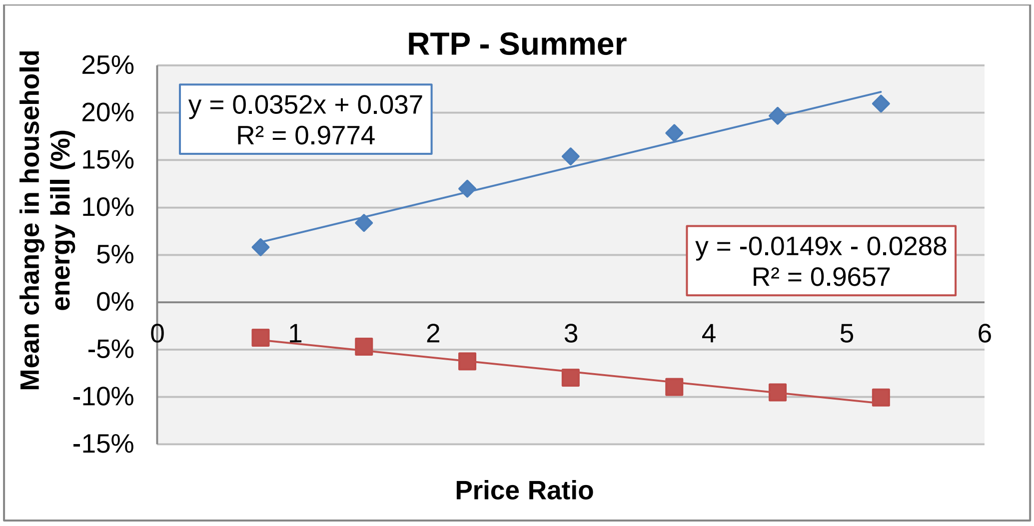


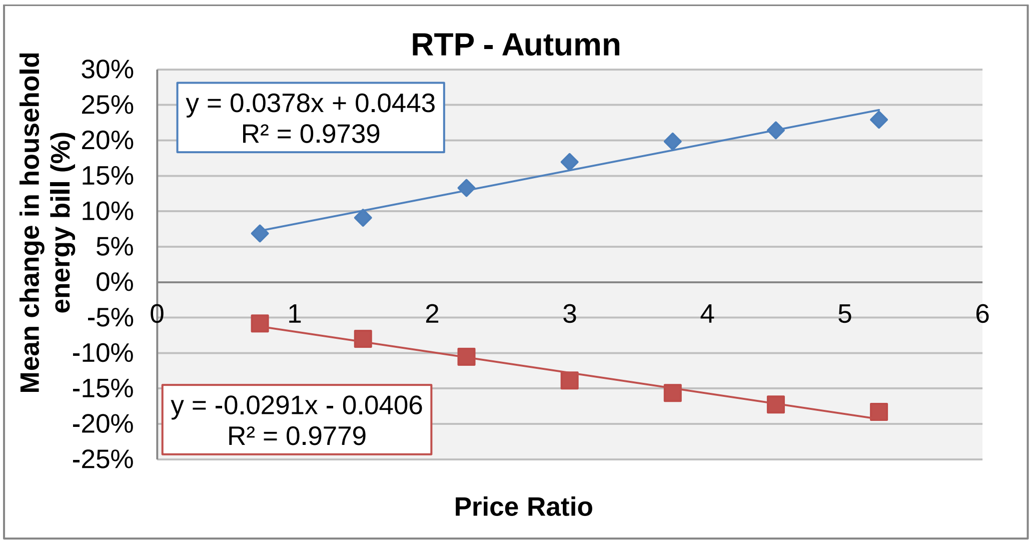

VToU - Summer
y = 0.0539x + 0.0731
R² = 0.9729
y = -0.0154x - 0.0221
R² = 0.9731
Mean change in household energy bill (%)
Price Ratio
40%
30%
20%
10%
0%
-10%
-20%
0
1
2
3
4
5
6

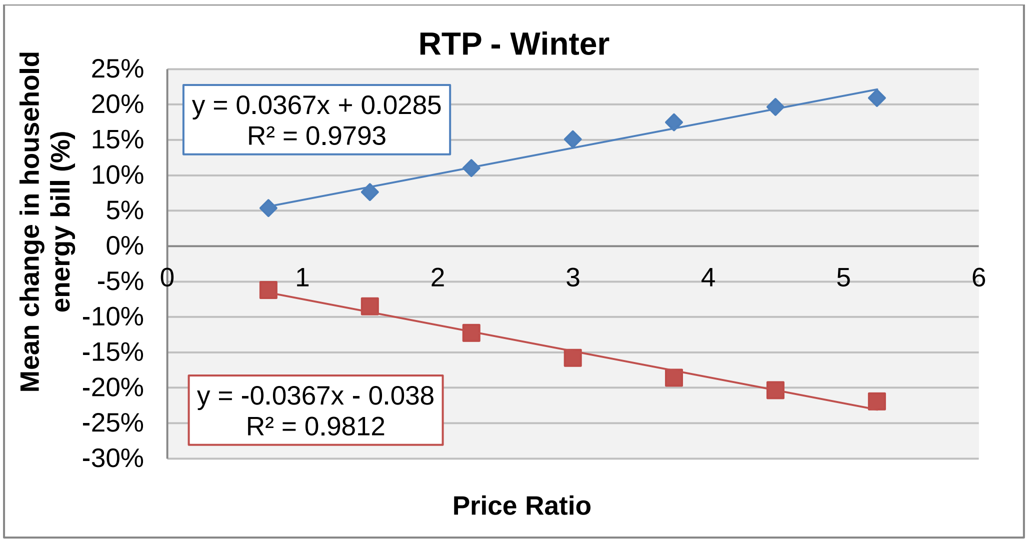

VToU - Autumn
y = 0.0441x + 0.0547
R² = 0.976
y = -0.0452x - 0.0548
R² = 0.9806
Mean change in household energy bill (%)
Price Ratio
40%
30%
20%
10%
0%
-10%
-20%
-30%
-40%
0
1
2
3
4
5
6

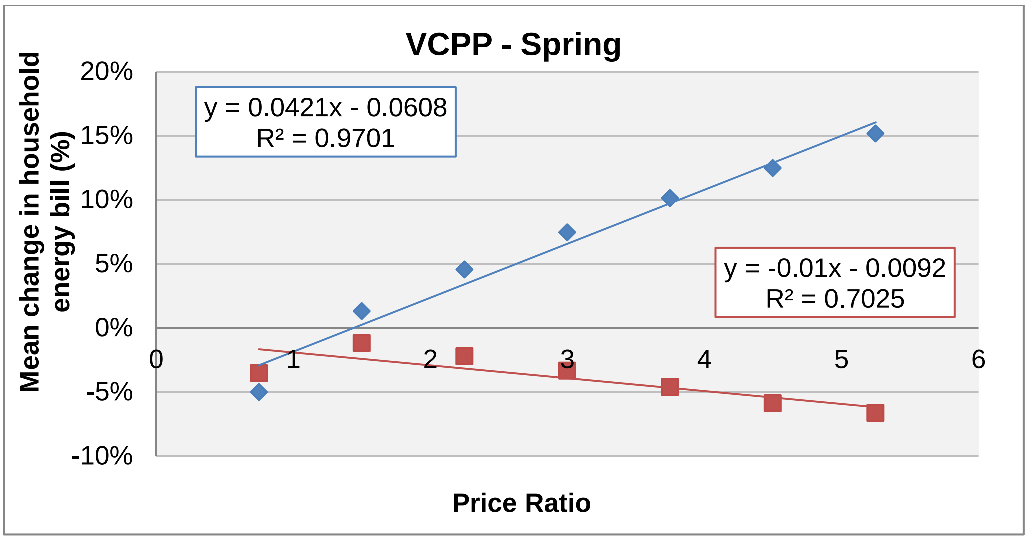

VToU - Winter
y = 0.0592x + 0.0552
R² = 0.981
y = -0.0545x - 0.0505
R² = 0.9827
Mean change in household energy bill (%)
Price Ratio
50%
40%
30%
20%
10%
0%
-10%
-20%
-30%
-40%
0
1
2
3
4
5
6

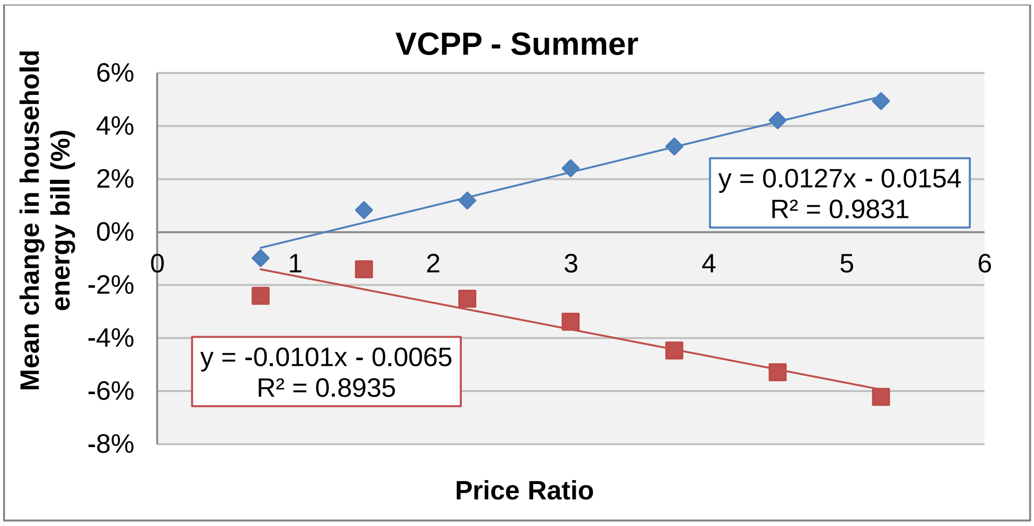

RTP - Spring
Mean change in household energy bill (%)
40%
30%
20%
10%
0%
-10%
-20%
-30%
0
1
2
3
4
5
6
y = 0.055x + 0.0483
R² = 0.9772
y = -0.0294x - 0.0331
R² = 0.9781
Price Ratio

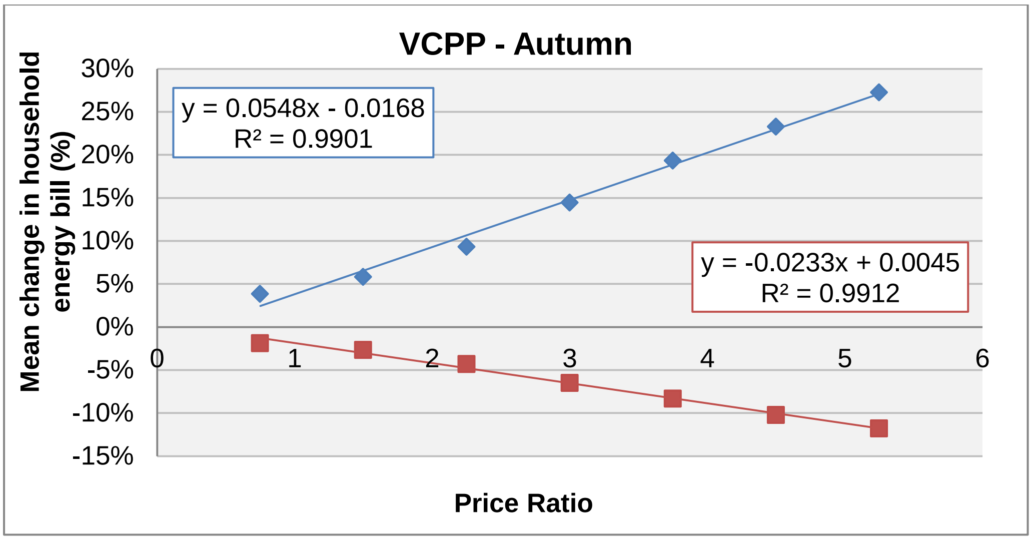

RTP - Summer
Mean change in household energy bill (%)
25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
0
1
2
3
4
5
6
y = 0.0352x + 0.037
R² = 0.9774
y = -0.0149x - 0.0288
R² = 0.9657
Price Ratio


RTP - Autumn
Mean change in household energy bill (%)
30%
25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
0
1
2
3
4
5
6
y = 0.0378x + 0.0443
R² = 0.9739
y = -0.0291x - 0.0406
R² = 0.9779
Price Ratio

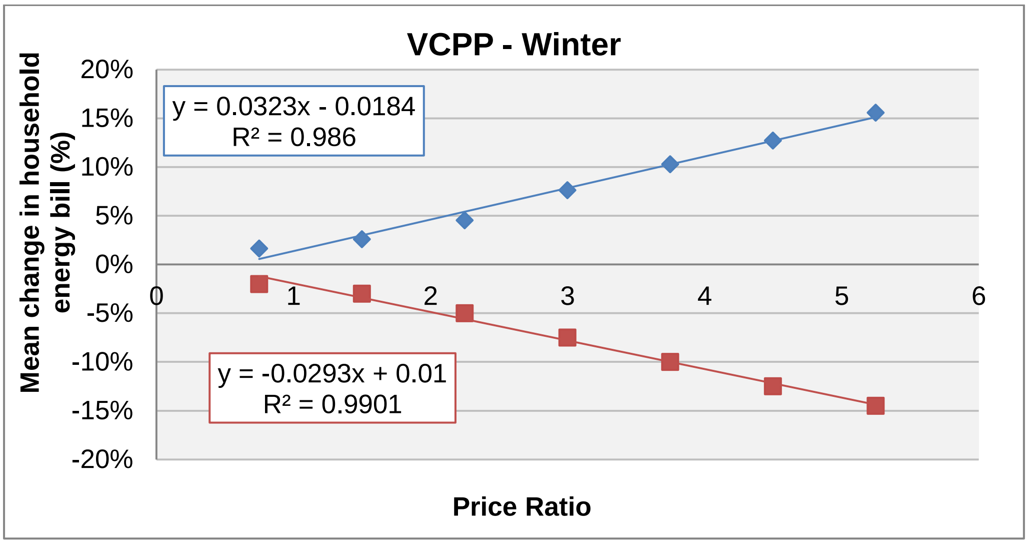

RTP - Winter
Mean change in household energy bill (%)
y = 0.0367x + 0.0285
R² = 0.9793
y = -0.0367x - 0.038
R² = 0.9812
25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
-25%
-30%
0
1
2
3
4
5
6
Price Ratio


VCPP - Spring
Mean change in household energy bill (%)
y = 0.0421x - 0.0608
R² = 0.9701
y = -0.01x - 0.0092
R² = 0.7025
20%
15%
10%
5%
0%
-5%
-10%
0
1
2
3
4
5
6
Price Ratio


VCPP - Summer
Mean change in household energy bill (%)
y = 0.0127x - 0.0154
R² = 0.9831
y = -0.0101x - 0.0065
R² = 0.8935
6%
4%
2%
0%
-2%
-4%
-6%
-8%
0
1
2
3
4
5
6
Price Ratio



VCPP - Autumn
Mean change in household energy bill (%)
30%
25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
0
1
2
3
4
5
6
y = 0.0548x - 0.0168
R² = 0.9901
y = -0.0233x + 0.0045
R² = 0.9912
Price Ratio



VCPP - Winter
Mean change in household energy bill (%)
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
0
1
2
3
4
5
6
y = 0.0323x - 0.0184
R² = 0.986
y = -0.0293x + 0.01
R² = 0.9901
Price Ratio