Assessing the Potential Impacts of Peak Load Reduction Interventions via Domestic Electrical Load Disaggregation

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Abstract

In response to a number of pre-existing and impending challenges facing the UK electricity grid, notably the reduction in electricity capacity margins and highly variable generation costs, there is growing interest in demand response actions which may help to reduce peak electricity demand at the local and national levels. This dissertation focuses on the potential of domestic interventions to reduce peak demand. Firstly, 1-minute resolution domestic electricity data is disaggregated into appliance types according to an algorithm developed for this project. Subsequently, three peak reduction interventions are modelled in order to identify the potential reductions which these interventions could result in. The three interventions which were considered were to supply low-energy lighting, switch off cold appliances and prohibit electric shower use during peak times. Upper bounds for each of these interventions were found to be 15%, 7% and 0.4% of peak electricity consumption for each of the interventions respectively. These results are deemed to be significant reductions in peak demand from the perspective of a distribution network operator and may serve to avoid or delay investments in network reinforcements.

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Contents

Abstract i

Acknowledgments ii

Index of Figures vii

Index of Tables xii

Nomenclature xiii

1. Introduction 1

1.1. Context 1

1.1.1. Variation in the Cost of Generation 1

1.1.2. UK Electricity Capacity Margin 2

1.2. Related Projects 3

1.2.1. Energy and communities project 3

1.2.2. SAVE project 3

1.3. Aims and Objectives 3

2. Literature Review 5

2.1. United Kingdom Smart Meter Roll Out 5

2.1.1. Scope of the UK Smart Meter Roll Out 5

2.1.2. Anticipated Costs and Benefits of the Program 5

2.1.3. Government Sources of Supporting Evidence 6

2.2. Smart Metering Case Studies 7

2.2.1. Introduction to Smart Metering Case Studies 7

2.2.2. Energy Demand Research Project 7

2.2.3. Electricity Smart Metering Customer Behaviour Trials 9

2.2.4. Advanced Metering Initiatives and Residential Feedback Programs 11

2.2.5. Perth Solar City Trials 13

2.2.6. Italian Smart Meter Roll Out 14

2.2.7. Qualitative Studies on Smart Meters 15

2.2.8. Analysis of Customer Reviews 15
2.2.9. Residential Engagement with Energy Conservation 16
2.2.10. The Importance of Smart Meter Interfaces 17
2.3. Domestic Electrical Load Disaggregation 18
2.3.1. Introduction to Load Disaggregation 18
2.3.2. Multivariate high-resolution methods 18
2.3.3. Probabilistic low-resolution methods 18
2.3.4. Characterising Appliance Loads 20
2.3.5. Delta Form of Load Profiles 20
2.3.6. Estimating Demand Responsiveness 21
3. Methodology 23
3.1. Overview 23
3.2. Dataset 23
3.3. Algorithm 24
3.3.1. Background 24
3.3.2. Data Preparation 25
3.3.3. Base Load 26
3.3.4. Heating Element Spikes 27
3.3.5. Electric Showers 30
3.3.6. Cold Appliances 30
3.3.7. Lighting 32
3.3.8. Uncharacterised 33
3.4. Analysis 33
3.4.1. Appliance Load Profiles 33
3.4.2. Peak Load Reductions 34
4. Results 35
4.1. Introduction to Results 35

4.2. Appraisal of the Algorithm 35
4.2.1. Base Load 35
4.2.2. Heating Elements 37
4.2.3. Electric Showers 39
4.2.4. Cold Appliances 41
4.2.5. Lighting 45
4.2.6. Edge effects 47
4.3. Analysis of Appliance Types 50
4.3.1. Total Profile 50
4.3.2. Base Load 51
4.3.3. Heating Elements 53
4.3.4. Electric Showers 53
4.3.5. Cold Appliances 54
4.3.6. Lighting 56
4.3.7. Uncharacterised Appliances 58
4.4. Aggregated Mean Profile 59
4.5. Peak Load Reductions 61
4.5.1. Introduction to Peak Load Reductions 61
4.5.2. Low Energy Lighting 61
4.5.3. Cold Appliance Shifting 62
4.5.4. Electric Shower Shifting 63
4.5.5. Combined Impact 64
5. Discussion 68
5.1. Review of Appliance Types 68
5.1.1. Base Load 68
5.1.2. Heating Elements 68
5.1.3. Electric Showers 70

5.1.4. Cold Appliances 71
5.1.5. Lighting 72
5.1.6. Uncharacterised 73
5.2. Alternative Data Resolutions 73
5.3. Conclusion 74
5.4. Future Work 74
6. References 75
7. Appendices 80
7.1. Appendix A – Lighting Fixtures by Type 80
7.2. Appendix B – Tumble Dryer Power Consumption Data 80
7.3. Appendix C – Time Periods Used to Determine Cold Appliance Parameters 80
7.4. Appendix D – Calculation of Theoretical Cold Appliance Load 82
7.5. Appendix E – Modern Fridge-Freezer Power Consumption Data 84

Index of Figures

Figure 1. Average of the cost of generation by settlement period during the 1st – 28th October 2011, Data source: (Elexon, 2014) 1

Figure 2. Predicted de-rated capacity margins for the Reference Scenario and associated demand sensitivities in the UK, image Source: (Ofgem, 2013a).............................. 2

Figure 3. Total percentage responsiveness which is identified as possible at that time of day (Hamidi, et al., 2009) 21

Figure 4. Screenshots to show the initial data manipulation processes occurring during the algorithm. In particular showing the transformation of the dataset to a matrix format 26

Figure 5. Hypothetical example of heating element spike using artificial data. In this example three identical spikes in terms of intensity (2 kW) and duration (60 seconds) are shown as they would appear in the aggregated data if a) all 60 seconds of activity fell within the same 1-minute interval, b) the first 15 seconds of activity appeared in one interval and the remaining 45 appeared in the consecutive interval and c) the 60 seconds of activity bridged the two aggregated intervals evenly. 29

Figure 6. Representative example of a cold appliance cycle using artificial data. In order to show the important parameters used to characterise a cold cycle 31

Figure 7. Graph to show the various running averages which were considered for the cold cycling stage of the algorithm... 31

Figure 8. Recorded power consumption of house 001 from 1st - 28th October 2011 at 1 minute intervals. Axis maximum of 1000 W has been chosen to highlight base load data which has led to peaks being truncated.. 36

Figure 9. Base load power consumption identified by the algorithm for daily intervals from 1st - 28th October 2011.. 36

Figure 10. Power consumption for house 001 on the 8th Oct 2011 between 06:00 and 08:30 37

Figure 11. Power consumption data from house 022 for the 21st October 2011. Where total minus base load represents the total profile with the base load for that day subtracted and total minus heating elements represents the total profile minus the base load and minus the heating element profile. 38

Figure 12. Power consumption data from house 008 for the 8th October 2011. Where total minus base load represents the total profile with the base load for that day subtracted and total minus heating elements represents the total profile minus the base load and minus the heating element profile. 38

Figure 13. Distribution of the power consumption of electric shower events observed by the algorithm for 1st - 28th October 2011 in house 108 40

Figure 14. Distribution of the duration of electric shower events observed by the algorithm for 1st - 28th October 2011 in house 108 40

Figure 15. Power consumption data from house 026 for the 8th October 2011 between 00:00 and 08:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles. 42

Figure 16. Power consumption data from house 001 for the 21st October 2011 between 00:00 and 08:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and the two component cold cycling profiles. 43

Figure 17. Power consumption data from house 119 for the 16th October 2011 between 16:00 and 23:59. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles. 44

Figure 18. Power consumption data from house 029 for the 10th October 2011 between 00:00 and 10:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles. 45

Figure 19. Average power consumption profiles of uncharacterised appliances for house 015 from the 1st – 28th October 2011 and 1st – 28th June 2011 between 17:00 and 23:59. Here the Difference plot represents the assumed lighting load profile for this property in October. From left to right the vertical dashed lines represent median sunset in October and median sunset in June 46

Figure 20. Average power consumption profiles of uncharacterised appliances for house 014 from the 1st – 28th October 2011 and 1st – 28th June 2011. Here the Difference plot represents the assumed lighting load profile for this property. From left to right the vertical dashed lines represent median sunset in October and median sunset in June 47
Figure 21. Graph showing the heating element profile and associated standard deviation margins between 00:00 and 00:59 demonstrating edge effects observed in the heating element profile 48
Figure 22. Graph showing the cold appliance profile and associated standard deviation margins between 00:00 and 00:59 demonstrating edge effects observed in the cold appliance profile.. 49
Figure 23. Graph showing the cold appliance profile and associated standard deviation margins between 22:00 and 23:59 demonstrating edge effects observed in the cold appliance profile.. 50
Figure 24. Typical total profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation.. 51
Figure 25. Typical base load profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 52
Figure 26. Average daily base load value for all properties in the sample from the 1st – 28th October 2011. 52
Figure 27. Typical profile of heating element appliances (minus electric showers) for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 53
Figure 28. Typical electric shower profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 54
Figure 29. Typical cold appliance profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 55
Figure 30. Typical lighting profile for a subset of 10 properties from the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 and

1st and 28th June 2011. Additionally showing the mean profile plus and minus one standard deviation 56
Figure 31. Comparison of the average lighting profile observed across the 10 properties as they were observed and as modelled under the low energy lighting intervention 57
Figure 32. Typical uncharacterised profile (with lighting removed) for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 58
Figure 33. Typical uncharacterised plus lighting profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation 59
Figure 34. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 not including lighting 60
Figure 35. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 including lighting 60
Figure 36. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the low energy lighting intervention 61
Figure 37. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the cold appliance intervention 62
Figure 38. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the cold appliance intervention and highlighting the possible surge in power once appliances are switched back on 63
Figure 39. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the electric shower intervention 64

Figure 40. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of all interventions combined..65
Figure 41. Average total demand profile plotted in black and showing the percentage of the total load which is made up by each appliance type for each time during the day. Highlighting the percentage reduction from which could be achieved at each point during peak..66
Figure 42. Average total power demand during peak times and showing the power consumption which could be avoided during peak times from each intervention 66

Index of Tables

Table 1. Results of the housing survey which indicate the proportion of low energy lighting found in the properties used for the lighting analysis. *Data was not available for this property and the average of the sample was used........................57
Table 2. Summary of the electricity consumption associated which each appliance type 59
Table 3. Summary of the peak load reductions which could be achieved from each of the interventions...67

Nomenclature

£/MWh - Great British Pounds per Mega-Watt Hour

€c/kWh - Euro Cents per Kilo-Watt Hour

CO_2 - Carbon Dioxide

DCC - Data and Communications Company

DECC - Department of Energy and Climate Change

DNO - Distribution Network Operator

DSM - Demand Side Management

ECC - Energy and Climate Change Committee

EDRP - Energy Demand Research Project

ESRC - Economic and Social Research Council

IHD - In Home Display

kW - Kilo-Watt

kWh - Kilo-Watt Hour

Ofgem - Office of Gas and Electricity Markets

p/kWh - Great British Pence per Kilo-Watt Hour

RTD - Real Time Display

SAVE - Solent Achieving Value from Efficiency

SSE - Scottish and Southern Electric plc.

ToU - Time of Use (Tariff)

UK - United Kingdom

US - United States

W - Watts

1. Introduction

1.1. Context

In response to a number of significant challenges facing the electricity industry at present and throughout the coming decades, there has been significant interest shown from governments and industry players to understand the impact which domestic demand side response and associated domestic electricity efficiency measures could play in resolving these issues.

1.1.1. Variation in the Cost of Generation

Despite most customers being charged a flat rate for domestic electricity of around 13.5 p/kWh (£135/MWh) (Energy Saving Trust, 2014a) there is substantial variation in the cost of generating electricity during a typical day. This variation in the cost of generating electricity is shown below (Figure 1), for the average of 1st – 28th October 2011. The general trend observed is a trough in generating costs overnight whilst demand is low, followed by a small morning peak and a larger evening peak. Over the course of this month peak generation costs were 2.4 times greater than base generation costs (Elexon, 2014). This variation arises from the requirement for different types of power plant to be active in order to meet demand and in particular the cost of the fuels which are used by the different plant types.

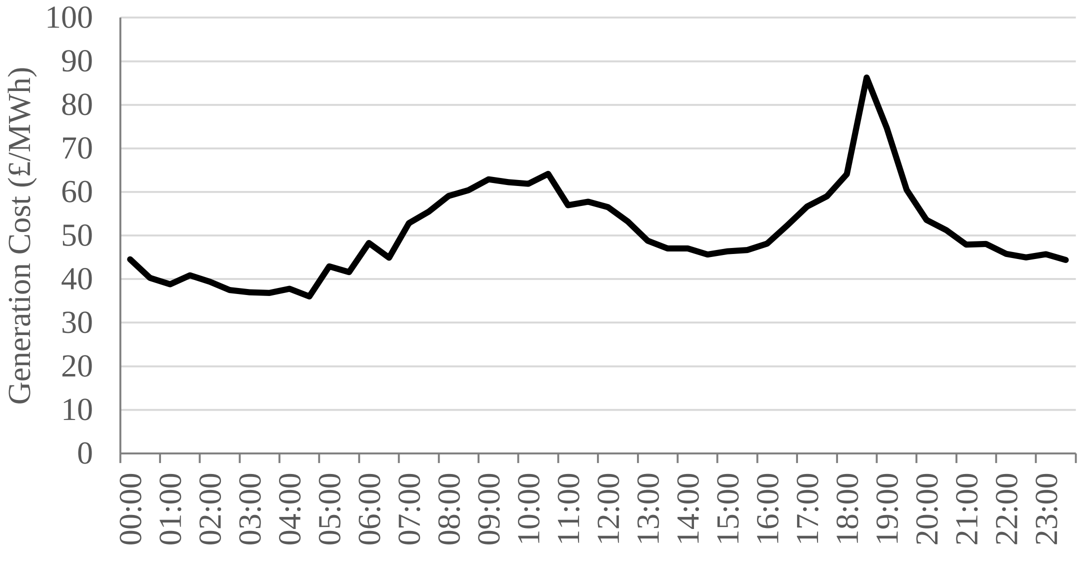

Figure 1. Average of the cost of generation by settlement period during the 1st – 28th October 2011, Data source: (Elexon, 2014)

This large variation in generating costs provides the basis of time of use (ToU) electricity tariffs which would see customers charged more for using electricity during peak times, encouraging a shift in electricity usage to off-peak times and as a result smoothing the peaks and troughs.

1.1.2. UK Electricity Capacity Margin

In recent years the gap between plant capacity and peak demand, known as the electricity capacity margin, has been shrinking which could lead to the risk of blackouts in the United Kingdom (UK). The major causes of the shrinking electricity capacity margin are the decommissioning of ageing power plants, increased dependence on gas imports and tough environmental targets (Ofgem, 2013a; Royal Academy of Engineering, 2013). This problem is summarised in a recent report by the Office of Gas and Electricity Markets (Ofgem):

> *"We continue to expect that margins will decrease to potentially historically low levels in the middle of the decade and that the risk of electricity customer disconnections will appreciably increase, albeit from near-zero levels." (Ofgem, 2013a)*

Analysis into future trends on the electricity capacity margin suggests that the de-rated capacity margin[1] will continue to decrease for a further 2 years (Figure 2).

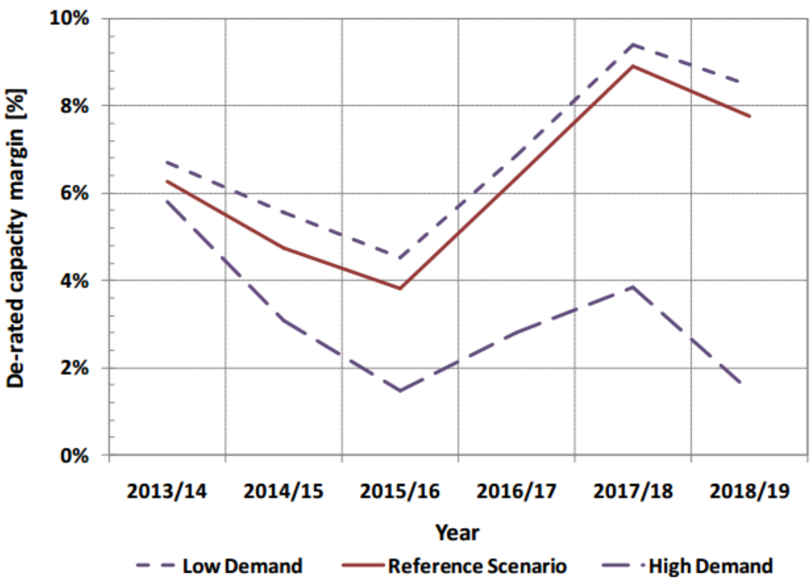

Figure 2. Predicted de-rated capacity margins for the Reference Scenario and associated demand sensitivities in the UK, image Source: (Ofgem, 2013a)

The trend is expected to trough in 2015/16 at which point the capacity margin will begin to grow again. The growth in capacity margin after 2015/16 is attributed to an anticipated decrease in peak demand due in part to energy efficiency measures (National Grid, 2013).

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[1] The de-rated capacity margin considers the average excess in supply (compared to winter peak demand) rather than the absolute plant capacity, an important distinction as the proportion of intermittent generation sources on the grid increases.

1.2. Related Projects

1.2.1. Energy and communities project

The data for this project has kindly been provided by a previously running project titled, “The role of community-based initiatives in energy saving”. This project was undertaken by researchers at the Universities of Southampton, Reading, Exeter and Westminster and funded by the Economic and Social Research Council (ESRC) (ESRC, 2014a).

The energy and communities project provided two groups of properties with loft and cavity wall insulation. Additionally, the test group was involved in an ongoing community project to increase awareness and educate participants on using less energy. The aim of the project was to identify the impact that a community based initiative could have on domestic energy usage reductions (ESRC, 2014a). For the purposes of the energy and communities project, power readings were recorded at short (1-second) time intervals for a sample of 175 dwellings (Bardsley, et al., 2013).

1.2.2. SAVE project

The purpose of the current project is to inform the potential peak load reductions which may be achieved by the upcoming Solent Achieving Value from Efficiency (SAVE) project, by focusing on a real dataset provided by the ‘Energy and Communities’ project.

The challenge addressed by the SAVE project is to identify the extent to which energy efficiency interventions can contribute to peak demand reduction. More specifically, whether energy efficiency interventions can delay or mitigate the need for a distribution network operator (DNO) to invest in network reinforcements when substations are close to reaching peak capacity (Ofgem, 2013b).

1.3. Aims and Objectives

This project will attempt to predict the impacts energy efficiency interventions could have on domestic electrical demand profiles by characterising the demand profile of a number of dwellings from an existing dataset into its component appliance parts and modelling demand reductions.

The project aim will be achieved according to the following objectives:

1) Formulate an algorithm which is capable of deconstructing measured electricity usage profiles of dwellings into their component appliance parts.

2) Apply this algorithm to a known dataset which was collected for the “Energy and Communities” project, in order to identify the appliance use profile of these properties.
3) Calculate the total reduction in peak electrical power that could be achieved for these properties under a range of interventions.
4) Provide an estimate of the demand reduction that could be achieved by a “SAVE” type intervention following energy efficiency approaches.

2. Literature Review

2.1. United Kingdom Smart Meter Roll Out

2.1.1. Scope of the UK Smart Meter Roll Out

Smart meters represent a significant opportunity for electricity networks across the world to increase awareness of electricity usage among the domestic consumers attached to these networks.

Over the course of the last 4 years the UK government has been involved in a consultation process on the potential roll-out of smart meters. The result is a plan to update all 53 million gas and electricity meters in the UK with 'smart' versions by visiting 30 million homes and small businesses (DECC, 2013a). The responsibility for the roll-out lies with energy suppliers who are required, where it is cost-efficient to do so, to complete the installation across the entire country by 2020, however the government does acknowledge that this may pose a significant challenge and accept a completion rate of 99.25% by 2020 (Energy and Climate Change Committee, 2013). In order to conduct the roll out as economically as possible the government suggests that energy suppliers should co-operate in order to bring about the greatest possible level of efficiency for the project.

In order for the smart meters to meet the anticipated demands of the future 'smart grid' all smart meters which are to be installed need to be capable of meeting the following functional requirements. They must be able to record and register voltages which would allow them to detect power outages, they must have load control capabilities in order for network operators to potentially be able to remotely control domestic loads in the future, they must be suitable for implementing ToU tariffs and they must be able to communicate between the data and communications company (DCC)[2] and the consumers in order for a variety of demand side management strategies to be implemented at a later stage (Energy and Climate Change Committee, 2013).

2.1.2. Anticipated Costs and Benefits of the Program

The government have outlined a range of qualitative benefits for consumers following the roll-out of smart meters, which include the following:

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[2] The DCC is a company which will be appointed by the government to handle all the data associated with smart meters. It was decided that one company would be responsible for all data, in order to facilitate easy switching for consumers between different energy suppliers with the aim of increasing competition in the energy market (Energy and Climate Change Committee, 2013).

- *"Smart meters give you near real time information on energy use – expressed in pounds and pence"*
- *"You will be able to better manage your energy use, save money and reduce emissions"*
- *"Smart meters will bring an end to estimated billing - you will only be billed for the energy you actually use, helping you budget better"*
- *"Easier switching - smoother and faster to switch suppliers to get the best deals"*

These are the benefits listed on the government's website (DECC, 2013b).

The economic case set out by Ofgem suggests the programme will cost £11.3bn and will provide benefits worth £18.6bn. Benefits are presumed to be derived mostly from energy usage reductions and savings in industry processes. All costs and benefits will be absorbed into consumer's energy bills (DECC, 2011). A detailed breakdown of the cost-benefit analysis has proved difficult to source, a concern echoed by members of the Energy and Climate Change Committee (ECC), who have requested that the Department of Energy and Climate Change (DECC) publish further information relating to the benefits of a smart grid (Energy and Climate Change Committee, 2013).

Overall, DECC assumes a bill saving of around 2.8%, however it is uncertain how much of this comes from domestic energy efficiency interventions, time of use tariffs or reduced administration costs for energy suppliers.

However, the smart meter impact assessment states the following 2 benefit categories. The first is improved information to the network which is made up of reductions in electricity losses, more information for targeted investment in grid strengthening and more efficient management of power outages. These benefits are believed to be around £1bn (presumably per year, although this is not explicitly stated anywhere). The other benefit category considered by the impact assessment are related to load shifting due to time of use tariffs resulting in reduced peak plant operation. These benefits are estimated to be around £900m (again it is not stated whether this is total of per year) (Energy and Climate Change Committee, 2013).

2.1.3. Government Sources of Supporting Evidence

A number of large scale trials and reviews have been conducted to inform the UK smart-meter roll-out. UK trials conducted directly by Ofgem include the 'Energy Demand Research Project', 'Low Carbon Networks Fund' and 'smart metering consumer research report'. Further research from outside the UK which has guided the cost-benefit analysis includes studies from the ‘European Smart Metering Industry Group’ the Irish ‘Commission for Energy Regulation’ and the United States (US) ‘Advanced Metering Initiatives and Residential Feedback Programs’ (DECC, 2013b). A number of these studies will be reviewed in the next section, along with other relevant studies from the literature.

2.2. Smart Metering Case Studies

2.2.1. Introduction to Smart Metering Case Studies

In order to gain insights into the potential impacts that smart metering may have, a number of case studies, trials and reviews have been analysed to determine the potential scale of energy usage reductions resulting from interventions, along with any areas where further research may be required and any possible flaws in methodologies. This review will begin by discussing the studies which were considered by the UK government during the UK smart meter roll-out consultation. Next, a number of additional large scale international trials will also be considered, and finally, some more targeted qualitative research will be presented.

2.2.2. Energy Demand Research Project

The Energy Demand Research Project (EDRP) was run by DECC and Ofgem as a series of trials between 2007 and 2010. The intention of the project was to identify and quantify measures which may be effective in reducing overall domestic energy use or peak energy use, with the main focus of the measures being on how consumers react to improved feedback relating to their energy usage (AECOM, 2011).

The interventions which were considered included: energy efficiency advice, historic consumption information, benchmarking against other households, engagement through target setting, smart meters, real time displays, financial incentives, digital media information and in one trial a community based financial incentive was also tested. The various trials had a total sample of 60,000 households spread across the UK of which 18,000 had smart meters installed (AECOM, 2011).

An important finding from the trial was that for almost all interventions across the various trials there was no significant reduction in electricity demand if a smart meter was not installed in the household. The only exception were interventions involving clip on real time displays which provide users with detailed feedback anyway and benchmarking which found a small reduction in the Scottish and Southern Electric (SSE) trial only, albeit the only trial in which this intervention was tested (AECOM, 2011).

Interventions in households where a smart meter was present were generally more successful, the report suggests this could be attributed to receiving the technology itself, options available with the smart meters and more frequent and accurate feedback and billing (AECOM, 2011).

Real time displays (RTDs) provide household with immediate information on their energy usage and can alert consumers to current high levels of consumption or high base loads, hence they should provide a means for consumers to curb their energy use through improved awareness. In the EDRP the combination of RTDs with smart meters yielded energy usage reductions of around 3% with reductions persisting to the end of the trials from 2007-2010 (AECOM, 2011). It is believed that accompanying advice relating to the smart meter and RTD is very important for the intervention to yield a demand reduction as consumer engagement is key and this can only be achieved through a useable display, a concept which will be discussed later. Surveys identified that the most successful displays showed information related to cost rather than power or energy and that CO_2 emissions were not perceived as particularly useful, which seems to follow a pattern of how familiar consumers are with a metric. The literature review for this study made the following observations which weren't quantified. The first was that RTDs may be useful for confirming an energy reduction action rather than initiating one and the second is that RTDs are used by consumers to check all appliances are off before bed and when leaving the house. Audible alarms for high consumption were not received positively and provided no electricity savings. However, traffic light systems were received much more positively (AECOM, 2011).

A number of trials were conducted which focused on energy advice and historic feedback. These provided mixed results from 0% - 5% reductions with the most successful trial being one which provided advice progressively over the course of the trial (monthly instalments) in short easy to digest statements. Whereas a less successful trial provided all information in a more detailed booklet at the start of the trial (AECOM, 2011).

> *"The message is that advice should be provided as a fundamental requirement, and historic feedback can be useful, but the details of delivery, and combination with other interventions are critical." (AECOM, 2011)*

A number of other interventions were considered during this project, the results of which are summarised here. Interventions based on financial incentives were mostly unsuccessful at reducing overall energy consumption and the effects only last as long as the incentive is in place. Largely due to the lack of engagement with the websites, web based interventions showed no real positive effects. ToU tariffs studied in these trials saw effects of up to 10%, notably, larger shifts were observed at weekends and in smaller households. No total demand reduction was observed in ToU trials and data related to which appliances were shifted was not gathered, this is an important area for further research. Further research should also be conducted to identify which demographic groups were more or less likely to reduce their consumption (AECOM, 2011).

> *"The optimum tariff levels and ratios, and the role of advice and technology in supporting behaviour change, are as yet poorly understood." (AECOM, 2011)*

Whilst initial research has been conducted into the area of ToU tariffs by these trials, there is a clear gap in knowledge which could provide an interesting avenue for further research.

2.2.3. Electricity Smart Metering Customer Behaviour Trials

Through its Commission for Energy Regulation the government of Ireland has conducted extensive research into customer behaviour to produce *'one of the most statistically robust smart metering behavioural trials conducted internationally to date'.* (Commission for Energy Regulation, 2011).

There were two key stages to the project, a benchmarking stage and a trial stage. Benchmarking was used to identify a 'typical' energy consumption over a 6 month period prior to the start of the interventions which was then followed immediately by a trial stage where the interventions were tested for a year (Commission for Energy Regulation, 2011). Households were offered to take part in the trial via a slip which was torn off (presumably attached to their bill) and overall the trial achieved a 30% response rate.

Surveys were conducted with each of the 5,375 households prior to and after each trial in order to identify any changes in attitude and to inform the allocation of households to appropriate interventions. Particular attention was paid throughout the recruitment process to ensure that the participants were representative of the national profile (Commission for Energy Regulation, 2011).

The trials were a combination of different time of use (ToU) tariff levels and a range of demand side management (DSM) interventions, including; bi-monthly energy statements, monthly energy statements, electricity monitors or a financial incentive for overall load reduction and weekend tariffs. They also received fridge magnets with the rates for each ToU band for their specific tariff group.

For the trial the ToU tariffs were designed so that the average consumer who made no changes to their electricity consumption would not be penalised financially. The different rates were allocated according to measured system demand peaks in three tiers, 11pm – 8 am (night rate), 8am – 5pm (day rate), 5pm – 7pm (peak rate) and 7pm – 11pm (day rate). The range of rates for different tariff groups was significant (12-20 €c/kWh for the most stable tariffs, up to 9-38 €c/kWh for the most variable tariffs). There is still no strong evidence to suggest any of the ToU tariffs outperform any of the others, hence there is no evidence for a 'tipping point' at which ToU tariffs suddenly become effective (Commission for Energy Regulation, 2011).

> *"Demand for peak usage estimated as being highly inelastic relative to price." (Commission for Energy Regulation, 2011)*

The overall results observed from these trials are as follows: a 2.5% reduction in overall electricity usage and an 8.8% reduction in peak electricity use. The optimum combination for reducing electricity usage was bi-monthly billing, energy usage statement and an electricity monitor which resulted in a peak shift of 11.3% (Commission for Energy Regulation, 2011).

A number of other more general observations were made as a result of these trials:

- All but one of the intervention trials provided statistically significant energy usage reductions.
- It was observed that households with greater energy consumption tend to provide the largest overall energy savings.
- Where peak load shifting has occurred it is usually towards post peak and night usage, as opposed to pre-peak. This is logical since consumers can't use energy before they arrive home.
- The fridge magnet and stickers which demonstrated information related to the ToU tariff bands were deemed to be successful in relating the information regarding tariff bands, with an 80% recall rate.
- The benefits of the trial were believed to be restricted to behavioural change and not the investment in more energy efficiency products.
- 82% of participants made some behavioural change with regards to how they use electricity in order to gain financial benefit from the ToU tariff.

The report also comments on a potential barrier to interventions being related to the relatively small financial benefits associated with behavioural change to reduce peak load, so focussing on savings may not prove to be particularly useful.

> *"Barriers to peak reduction relate to the difficulty of linking behaviour change to bill reduction. These perceptions may have contributed to the current recorded reduction. This may be hard to address due to exaggerated expectations of savings and similar exaggerated expectations of consequences if reduction is not achieved." (Commission for Energy Regulation, 2011)*

Additionally, the report comments on the link between energy usage and socio-economic factors. They postulate that more affluent households (which are typified by higher social grade and educational achievement) are likely to be able to reduce their energy usage more, as they have a higher baseline energy usage. However due to their relative affluence the financial savings gained from reducing consumption would be lower as a proportion of their earnings.

> *"Households headed by individuals with greater educational achievement or social grade achieved higher levels of reduction than those with lower levels. This was in part related to the typically higher level of usage associated with these households. Therefore, the impact of education or social grade on the ability to gain benefit from the tariffs is limited" (Commission for Energy Regulation, 2011)*

2.2.4. Advanced Metering Initiatives and Residential Feedback Programs

The 'Advanced Metering Initiatives and Residential Feedback Programs' report is a meta-review of feedback based energy efficiency studies between 1974 and 2010 in developed countries carried out by the American Council for an Energy-Efficient Economy in the US (Ehrhardt-Martinez, et al., 2010).

Average savings from feedback measures are found to be in the range of 4% - 12%, with direct feedback, such as real time displays more successful than indirect feedback which occurs post consumption. Measures which provide feedback at regular intervals are more successful than when feedback is provided over longer timeframes, for instance with energy bills. They also observe that direct feedback is more effective if additional information is provided alongside total consumption. Enhanced billing achieved 5.5% and real time feedback achieved 7%. However, for more recent studies focusing on just the US, energy savings were lower than the averages recorded across the entire sample of studies (Ehrhardt-Martinez, et al., 2010).

They state that the average overall energy savings are lower for programs targeting load reduction rather than energy efficiency, as would be anticipated. However, the total reduction for load shifting programs was around 3% on average compared to around 10% for conservation measures (Ehrhardt-Martinez, et al., 2010).

They comment that the overall impact of a particular intervention is not solely based on the average energy savings associated with that intervention but also on the uptake rate associated with intervention. Intuitively, the intervention which worked on an opt-out basis as opposed to an opt-in basis had higher participation rates and hence could achieve higher overall energy usage reductions. When participation rates are factored into energy usage reduction statistics the enhanced billing intervention reduces to 2% and real time feedback with additional information reduces to 6% (Ehrhardt-Martinez, et al., 2010).

As noted in other studies the largest savings are likely to come from combinations of measures, not from feedback devices alone, such as in-home displays (IHDs) plus personalised recommendations (Ehrhardt-Martinez, et al., 2010).

It is believed there are 3 main ways that consumers save energy having taken part in a feedback program. The first is to modify their behaviour, the second is low-cost energy stocktaking such as replacing energy inefficient bulbs and the third is to invest in more energy efficient appliances such as dishwashers. It is suggested that the main energy savings are achieved from behavioural change (Ehrhardt-Martinez, et al., 2010).

Analysis of the time dependence of energy efficiency interventions suggests that long term interventions are likely to yield more modest savings than short term studies, 7.7% vs 10.1% in the studies considered. However, it is believed that the longer term studies consisted of a more representative sample of consumers. Further analysis on studies which considered time dependence within the study itself found that as long as feedback was maintained, energy savings persisted through time, and the authors of the report postulate that the lower energy savings associated with the longer term studies may be the result of seasonal effects. As most of the short term studies were carried out in summer months which had higher energy use due to air-conditioning systems, potential energy savings were greater (Ehrhardt-Martinez, et al., 2010).

The regional and temporal context of the case studies under review is also deemed to be an important factor in determining the energy saving potential of an intervention. For example they find that studies that were carried out from 1970-1990, during the ‘energy crisis era’ were likely to have higher energy savings than studies carried out between 1995 and 2010, the ‘climate change era’. They also found that studies with European consumers yielded higher energy savings compared to those in the US (Ehrhardt-Martinez, et al., 2010).

2.2.5. Perth Solar City Trials

A range of other large scale trials have been conducted across the world which were not reviewed by the UK government but which can provide further evidence on the impact of domestic energy efficiency measures, some of which are reviewed here.

Launched in 2009, the Perth Solar City Program tested a range of interventions in a sample of 16,000 properties in Perth and surrounding suburbs. The measures included automated air-conditioner demand response for reducing peak load, ToU tariffs, enhanced feedback from in home displays, home 'eco-consultations', behavioural change programs, community based social marketing and a number of measures to encourage the uptake of small scale renewables (Perth Solar City, 2012). Whilst some of these measures are not relevant in the UK domestic context, a large number of them can provide useful insights.

The most significant intervention for reducing peak electricity demand was the automated control of domestic air-conditioning units, this resulted in a peak reduction of 25% (Anda & Temmen, 2014). Whilst this intervention may not be directly transferable to the UK (due to the low penetration of air-conditioning units), it shows the large potential that automated control of energy intensive devices can have, so long as consumers have enough trust in suppliers to allow them to switch them off. As the number of heat pumps continues to rise in the UK, it is plausible that a similar system could be employed for these. Encouragingly, of the consumers who participated in this trial in Perth, 87% said they would be willing to participate in similar trials in the future, indicating that their comfort was unlikely to have been significantly impacted by the intervention (Perth Solar City, 2012).

The ToU tariff trials which were conducted involved a three tier rate system to distinguish between night time, day time and weekdays between 14:00 and 20:00, where there was a factor of 3 difference between the highest and lowest rates (Perth Solar City, 2012). This trial found that the average reduction in electricity was 5%, with a 9% reduction during peak periods. When coupled with an IHD, this rose to a 6% reduction in overall usage and a 13% reduction during peak periods (Anda & Temmen, 2014). Alone IHDs were estimated to reduce overall electricity usage by 1.5% and peak demand by 5% (Anda & Temmen, 2014).

A group of 3,500 participants were provided with a home eco consultations, in which a consultant would provide a 90 minute audit and discussion with residents to inform them on how to decrease their energy usage. This strategy resulted in a 12% reduction in overall electricity usage and an 8% reduction in peak demand (Anda & Temmen, 2014). This intervention was received very positively by residents with 87% of participants rating it positively (Perth Solar City, 2012). Whilst these results are very positive, no indication in the paper is given the longevity of this effect and hence it is not clear how long energy reductions would be expected to last for.

A similar strategy, of providing advice on energy efficient behaviour was assessed through the behaviour change program, in this case participants were given feedback and recommendations over the phone on various occasions. This trial saw slightly more modest results than the home eco-consultation of 7.5% overall electricity usage reductions and peak demand reductions of 7%. One group of participants was provided with a combination of the behaviour change program, home eco consultation and an IHD. In this trial total energy usage was reduced by 21% and peak demand reduced 17% which are very promising results and suggest that using multiple mediums to promote energy efficiency could be even greater than the sum of their parts (Anda & Temmen, 2014).

The entire Perth Solar City program was supported by an extensive marketing campaign including; cinema and print advertising, billboards, and sponsorship of local events. The effects of this marketing campaign are believed to have reached beyond just the properties who were involved in the individual trials to other households in the area. The 'ripple effect' of the marketing campaign is believed to be around 1.6% reduction in overall energy use (Perth Solar City, 2012).

2.2.6. Italian Smart Meter Roll Out

With a high penetration of smart meters in Italy there has been scope to conduct large scale analysis of domestic energy efficiency interventions. One such trial involves testing the efficacy of ToU trials to reduce electricity demand across a sample of 1446 households in northern Italy using one years' worth of data at 15 min intervals (Torriti, 2012). The tariff system segments electricity usage into time segments of peak and off-peak, where peak is between 08:00 and 19:00 on weekdays. The difference in rates is low, 9.9 €c/kWh and 7.1 €c/kWh for peak and off-peak respectively. The authors assume that appliance design and controls are constant between the 2 consecutive years.

In order to remove weather effects on electricity consumption, they remove any data points where there is a greater than 4°C difference between the two years for the same time and day slot. This exclusionary principle was responsible for removing around 7% of data from the dataset. Data was then aggregated across the dataset in order to be able compare the daily load profile under a standard tariff and a ToU tariff (Torriti, 2012).

Surprisingly they find that when using a ToU tariff consumption actually rises by 13.7%. The average household now pays 5.31 Euros per day (under ToU) compared to 5.43 Euros per day previously, a slight decrease as users shift their consumption away from peak times (Torriti, 2012).

The authors are very positive about the impact that ToU tariffs have had on load shedding during the morning peak. The peak which was originally between 8:00 and 8:30 has now been shifted to 6:45 to 7:15 and has reduced from around 0.75 kWh per 15 minute period to 0.71 kWh per 15 minute period. Whilst it is clear that there is a consumer response to the ToU tariff, the peak has essentially been moved from one point in time to another, whether this is beneficial would depend on whether non-domestic electricity use is also higher during the original peak. If not it may be more beneficial to have staggered prices during the shoulder period[3] (Torriti, 2012).

For the higher evening peak, it is clear that consumers are avoiding using electricity during peak times however as people are now waiting until after 19:00 to use electricity there is an increase in peak demand just at a later time. Across the 41 substations which were involved in this study, 75% actually experienced an aggravation of peak demand problems when moving to the ToU tariff (Torriti, 2012).

2.2.7. Qualitative Studies on Smart Meters

All of the trials described previously focus on identifying the average effect that an intervention has on a sample of households which is very important in determining the scale of the impacts each intervention may be able to provide overall. However, blanket roll-out of measures may not prove to be the most cost-efficient method of making energy usage savings. An alternative which has been considered through the qualitative work of the following authors may be useful in helping to identify households where certain measures show more promise than others.

2.2.8. Analysis of Customer Reviews

A recent paper by Buchanan et al, 2014, focuses on using product reviews for four electricity usage monitors obtained from an internet review site to identify benefits and drawbacks of real time displays. The reviews are analysed qualitatively to see how users respond to ‘smart

[3] The shoulder period is the time directly before or after the peak period

meters'. There are three key areas of interest for this study: Why do users want energy monitors? How do they interact with them? What is the outcome of the interactions? (Buchanan, et al., 2014).

By identifying patterns and common positive and negatives aspects of the meters Buchanan et al (2014) are able to identify some of the key benefits and drawbacks of using electricity monitors. According to their analysis consumers predominantly buy energy monitors for financial reasons and less so for environmental reasons, which suggests that people are more interested in how monitors would benefit them as opposed to how their consumption impacts the environment. They identify that when energy monitors are used successfully, the process works by enabling consumers to 'see' energy and bring energy usage into their consciousness whereas previously it was an abstract concept. Both of these points are consistent with findings from the EDRPs surveys that people are more interested in displays which show money, rather than energy or CO_2 emissions', as they can visualise it more easily and this is their primary motivation to reduce energy use (Buchanan, et al., 2014).

The authors claim that energy monitors encourage consumers to adopt the following actions: experiment with electricity use, save money, switch off appliances, buy more eco products and encourage others to use less energy.

The main drawbacks of electricity monitors which were identified by this study were technical difficulties with the monitors, inaccurate readings and that the monitors have a novelty effect which wears off eventually (Buchanan, et al., 2014). This means that it is important to create monitors which are easy to use, provide relevant and accurate information and to provide monitors in a situation where consumer engagement can be maintained through additional information.

2.2.9. Residential Engagement with Energy Conservation

Murtagh et al (2014) have recently published a paper which looks at how different households regard energy efficiency measures and energy usage in general. The authors believe that placing too much emphasis on the average energy usage reduction of a particular intervention is obscuring important patterns in the effects of interventions for individual households and hence is missing an important opportunity to target interventions more effectively based on household characteristics (Murtagh, et al., 2014). They focus on feedback via IHDs and adopt a qualitative methodology to arrive at their findings.

The sample consisted of 21 properties in different social, economic and geographic contexts around the south of the UK in which interviews were conducted with the residents. One of the key findings of the study was that the majority of households (17/21) who had an energy monitor for over 6 months were not using the IHD (Murtagh, et al., 2014). Despite the majority of the sample not using the IHD, they were actively trying to reduce their energy consumption.

> *"The IHD provided information and enabled behaviour change for some households but overall, the participants demonstrated energy saving behaviour before and outside of monitor usage, and drew on knowledge on electricity use beyond that offered by the monitor" (Murtagh, et al., 2014)*

Analysis of the interviews allowed the authors to categorise the households into 3 types in a 20:60:20 split as monitor enthusiasts : aspiring energy savers : energy non-active, a classification which they developed themselves. The four households which made up the monitor enthusiast group were largely motivated by a mixture of financial and environmental reasons for their engagement with the monitor saving energy, despite the four households coming from a range of income brackets. The aspiring energy savers were again largely interested in saving money and considered that even small savings were worth a small amount of effort. However, it was noted that there was a large range of engagement across this group. The final group showed very little interest in taking action to save energy despite in some cases acknowledging the moral requirement to do so (Murtagh, et al., 2014).

2.2.10. The Importance of Smart Meter Interfaces

A paper by Kerrigan et al (2011), is predominantly focused on the usability of smart meters and how people interact with them. They achieve this by setting users the task of retrieving particular information from a commonly used smart meter used across Italy by the energy company 'Enel', of which there are currently 32 million installed.

They find that 69% of the time users were unable to successfully retrieve the desired information from the smart meter (Kerrigan, et al., 2011). In general users blame themselves for failure to reach the desired information as shown by a survey at the end of the study, however a number of strategies are suggested which could improve the usability of this smart meter. The first of these strategies is to use symbology and language which is easy for the user to understand, in particular to avoid jargon such as "instantaneous power" and codes (Kerrigan, et al., 2011). Another useful addition to this meter would be the inclusion of a back button, in case users make a mistake whilst navigating the meter. Finally it is suggested that displays should be easy to read (perhaps including back lighting) and larger enough that text can spread across as few views as possible (Kerrigan, et al., 2011). These considerations are important as the design and usability of smart meters could have a significant impact on how well interventions based on smart meters can achieve energy savings through user engagement.

2.3. Domestic Electrical Load Disaggregation

2.3.1. Introduction to Load Disaggregation

In order to shed light on the composition of domestic load profiles, with the aim of identifying which appliances consumers are willing to shift away from peak times and consequently which appliances to target with intervention, a growing body of work has focused on domestic electrical load disaggregation. This involves using the total load profile of a property and attempting to separate the profile into component appliance parts. The methods used to achieve disaggregated loads vary depending on the resolution of the data (how frequently measurements are captured), the variables captured in each time step and external information available about the properties, along with the desired level of detail of the output, creating highly context specific methodologies. This review will assess a number of the common methods which appear in the literature.

2.3.2. Multivariate high-resolution methods

When high resolution data (meter readings recorded at 1 second intervals) for a number of variables is available it is possible to build highly accurate disaggregated load profiles, by searching for appliance ‘signatures’. A number of authors have published papers on this topic.

The method described in a paper by Chahine et al (2011) considers voltage and current which are turned into real and reactive power. Changes in the various features of the total load profile are detected and the relevant appliance is deemed to be turned on according to matching changes against an appliance signature database. The paper focuses on characterising different appliance signatures according to the probability distribution of a number of events (Chahine, et al., 2011).

Similarly a paper by Figueiredo et al (2012) looks at active power, reactive power and power factors to determine typical appliance signatures which can then be extracted from the load profile according to changes in the total demand profile (Figueiredo, et al., 2012).

2.3.3. Probabilistic low-resolution methods

In situations when high volumes of measured data are not able to be captured, for example if the sample of properties is very large, or it isn’t cost efficient to capture high resolution data for a large number of variables, then it is necessary to use alternatives means to estimate disaggregated load profiles.

Akbari (1995) suggested an algorithm to disaggregate hourly whole buildings loads by considering the temperature dependence of the electrical load at hourly resolution to determine the heating/cooling load. End use profiles are determined by firstly generating end use profiles from building audit data simulation and then adjusting these according to measured data (Akbari, 1995).

The first part of the algorithm is to separate the load into a temperature dependent part and a temperature independent part through regression analysis of outdoor dry bulb temp against load. The temperature independent part is then simply allocated to lighting and miscellaneous according to the results from the modelling conducted based on the site audit. They also state that the sum of disaggregated loads is constrained at hourly intervals to be the same as the measured load (Akbari, 1995).

They find that the algorithm is successful in predicting end use profiles up to around 30% of actual measured data when they compare derived against measured profiles. However, they also note that there is a substantial difference in the performance of the algorithm for two different building types (Akbari, 1995).

Similarly to Akbari (1995), Birt et al (2012) suggest a methodology which considers the temperature dependence of loads. The disaggregated profiles obtained in this paper are achieved through a statistical modelling methodology based on external temperatures to give a base load and active load estimate for individual properties, along with heating and cooling season gradients which could then be applied to external temperature data to estimate the active and passive loads of individual properties at the hourly resolution (Birt, et al., 2012).

A paper by Dominguez-Navarro, et al (2009) looks at load disaggregation as an error optimisation problem between pre-determined expected load profiles of different appliances and actual recorded data. The shape and size of each appliance profile is capable of changing during each movement of the optimisation algorithm, with the aim being to minimise the error between the modelled profile and the real data (Dominguez-Navarro, et al., 2009).

Work carried out by Richardson et al (2009) focuses on generating 1 minute resolution lighting data for dwellings, using a probabilistic method. The tool they have built is available as an excel example online. The method uses occupancy, irradiance data and sample household lighting characteristics in a Monty-Carlo simulation in order to generate a theoretical lighting profile (Richardson, et al., 2009).

2.3.4. Characterising Appliance Loads

Gruber et al (2014) propose a probabilistic method for determining the total demand of a property based and synthesised appliance type data, i.e. the aggregation of different appliance types. An interesting aspect of this research is the classification they have used for the various appliances found in dwellings, they focus on the common usage traits of each appliance to determine which category the appliance should be part of rather than the end use of the appliance, which leads to categories containing fridges and television base loads grouped together and television active use falling into another category (Gruber, et al., 2014). Identifying a practical grouping of appliances will be essential in this project.

An article by Kilpatrick et al (2011) describes a methodology for disaggregating domestic load profiles into appliance types. This methodology suggests adopting the following stages:

1) The first is to identify the minimum power usage of the property, it is assumed that this is representative of the standby power requirement or base load and can simply be subtracted from the profile.
2) Next the cold cycling component should be identified and removed according to the cold parameters (these will be discussed in the methodology section of this report).
3) Once the base load and cold cycling profiles have been removed large spikes associated with heating elements can be identified and removed. These are typified by short intense spikes in energy demand, leaving a profile consisting of lighting and residual loads.

This article provides an interesting starting point for the development of an algorithm suitable for this project. Particularly interesting are the categories of appliance type which are used (Kilpatrick, et al., 2011).

2.3.5. Delta Form of Load Profiles

Similarly to methodologies described in the section on multivariate high resolution methods, Liang et al (2010), look at a variety of electricity characteristics: Current, voltage and power, to create appliance signatures which can then be identified from within the total profile load profile.

An interesting aspect of this study is the way they consider both a snapshot form of the load, which is the total power, current, etc. observed at any one time, but also a delta form, which demonstrates the change that has occurred in the profile between one point in the time from the previous point. They postulate that as long as the snapshot interval is short enough (~1 s) then by considering the changes in load it may be possible to identify appliance signatures (Liang, et al., 2010). This could have potentially useful applications for this project as high resolution data is available.

2.3.6. Estimating Demand Responsiveness

A previous study on the demand responsiveness of different appliance types, uses the standard load profile types published by Elexon to estimate the total load profiles in an area of Bath, UK. The authors' then estimate the proportion of each load which could feasibly be impacted by a demand response action, in order to predict the demand responsiveness of domestic electricity throughout the day (Hamidi, et al., 2009). The findings from this study are presented in Figure 1Figure 3.

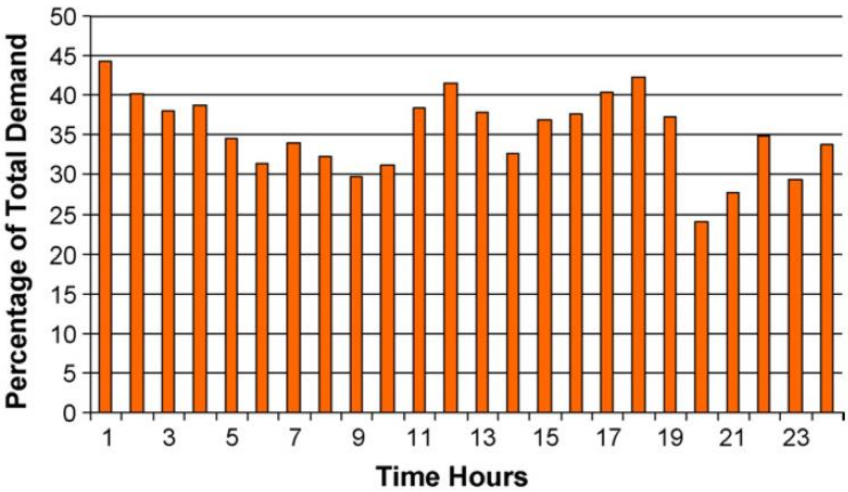


Figure 3. Total percentage responsiveness which is identified as possible at that time of day (Hamidi, et al., 2009)

The results from this study are interesting, in that they aim to provide an upper limit for what could be achieved from a generic set of interventions. One key weakness of the analysis which could be addressed by the current study is the use of synthetic data for the generation of appliance load profiles. Additionally by focusing on more specific interventions, the findings from the current dissertation could add interesting knowledge to the area.

A further study presented by Soares et al (2014) uses the number of dwellings in an area and the appliance ownership rate in order to simulate appliance load type profiles. These profiles are then used to determine the proportion of domestic energy in a particular area which could be shifted from peak, according to a set of assumptions (Soares, et al., 2014).

The assumptions are that loads with a thermostat can have the set points adjusted during peak, in order to save 5% of the energy, interruptible loads will have a reduction in electricity of 10% during peak, which will need to be repaid at a higher rate (15%) during off-peak periods. And that loads which can be shifted will only be used out of peak times (Soares, et al., 2014).

Interestingly, the authors identify various appliances whose energy consumption can easily be shifted away from peak. These appliances are washing machines, tumble dryers and dish washers (Soares, et al., 2014). They are particularly suitable for load shifting interventions since they generally only need to be used once per day for a short (1 – 3 hour) cycle and for the most part delaying this cycle wold not cause significant inconvenience to the user. Whilst these loads provide a significant opportunity for peak load reduction, the unpredictable nature of the appliance cycles would make them challenging to extract from a total load profile.

The authors' claim that savings of between 0.5% and 5% in peak load can be achieved (Soares, et al., 2014). This study is based on data from Portugal, where domestic load profiles are substantially different to the UK due to the use of air conditioning units in response to differences in climatic conditions. Similarly to the (Hamidi, et al., 2009) paper, the appliance load profiles are simulated based on more general data whereas this project aims to make predictions based on measured data.

3. Methodology

3.1. Overview

The main aim of this project was to estimate the maximum impact that a range of interventions could have on reducing the peak domestic electrical load, which occurs during the evening on weekdays.

This was achieved by disaggregating the total demand profiles for a number of properties into their constituent base load, cold appliance, heating element and lighting profiles and then aggregating the various appliance profiles across a sample of properties in order to determine the extent that each appliance type contributes to the electrical load peak. Once this has been determined, an upper bound for the impacts that a range of interventions could achieve is estimated. This then gives an estimate of the maximum impact that interventions could have on reducing peak electricity usage, this can inform the upcoming SAVE project.

The SAVE project aims to determine whether energy efficiency interventions can be used to relieve the strain on electricity substations which are close to reaching maximum capacity, as opposed to employing more traditional network reinforcement measures. The project aims to trial a range of interventions including technology deployment, commercial incentives and engaging residents. The technological measure, involves providing residents with low energy light bulbs in order to decrease electricity usage associated with lighting. Engagement measures are focused around using data to tailor engagement campaigns and commercial incentives involve creating a ToU tariff in order to encourage residents to shift their electricity usage away from peak times (Ofgem, 2013b).

3.2. Dataset

The data used in this project was provided by the energy and communities project which aims to identify the impact which community based initiatives can have on reducing energy consumption in dwellings (ESRC, 2014a; University of Southampton, 2014a). The project was undertaken by academics at the Universities of Southampton, Reading, Exeter and Westminster and was funded by the ESRC.

The dataset consists of high temporal resolution power readings for a sample of 175 properties over the course of 3 years from 2011 to 2013 (Bardsley, et al., 2013). Amongst other datasets, total electrical power usage for each of the households was collected for each one second interval during the trial, along with surveys and interviews conducted with each of the households. The survey data was gathered for the purpose of identifying relevant attributes which could be used to characterise households. Data was gathered using a commercial monitoring system called 'AlertMe'.

For the purposes of the current project the data has been aggregated into one minute intervals in order to reduce the data volume. However, by maintaining relatively high resolution, patterns of interest in the data have been preserved. These patterns are used to identify trends in electricity usage which can be used to identify different types of electrical load at a particular point in time.

The data aggregation and cleansing processes were carried by researchers working on the "Census 2022" project. This project aimed to identify alternative means of generating small area socio-economic indicators based on household electricity use to replace the previous time consuming and costly practise of 'census-taking' (ESRC, 2014b; University of Southampton, 2014b).

The time period of the data used for this project is the 1st - 28th October 2011 and for the purpose of determining the lighting load additional data from 1st - 28th June 2011 has also been used.

Within the overall dataset there were a large number of properties which had incomplete data for the period under investigation. Properties with substantial periods of missing data, i.e. more than a day or multiple gaps of more than an hour were rejected from the sample for this project. Fortunately it was still possible to select a sample of 51 properties which had sufficient data to proceed with the project.

3.3. Algorithm

3.3.1. Background

In order to disaggregate total load profiles into individual appliance type profiles for each property it was necessary to create an algorithm which could identify which types of appliance were likely to be active at any particular time interval.

With the 1 minute resolution data which was available for this project the decision was made to focus mostly on relational properties between the power usage at one time interval compared to the power usage at times prior to and following the interval of interest (the term 'interval of interest' will be used to describe a unique one minute interval which the algorithm is working on directly), as opposed to probabilistic methods based on time of day (more relevant with lower resolution datasets) which were only used to help determine the lighting load for each property at later stages in the analysis.

Due to the large volume of data involved in this project, the algorithm was designed to work as autonomously as possible, in order to minimise manual data analysis. With this in mind a tool was created in Microsoft Excel which was able to generate base load, heating element, electric shower, and cold appliance profiles from raw data with just a small number of parameters related to the cold cycling requiring updating.

3.3.2. Data Preparation

The algorithm which deconstructs the total load profile began by generating a matrix of power usage readings based on date and time, from the raw data which exists as a long list of meter readings for each minute interval across the month, as shown by Figure 4. In order to achieve this in Excel it is necessary to create separate values for the date and time from the combined date time stamp which was provided. The functions required for this are:

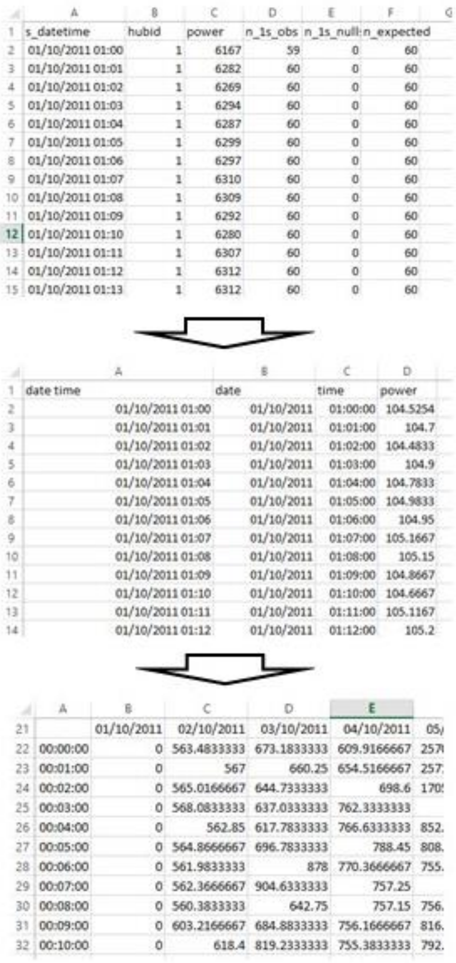
*"=INT(**CELL**)"*

which provides an integer value for the date and discounts the time element and:

*"=MOD(**CELL**,1)"*

which returns the decimal remainder once the integer has been subtracted and hence results in the time element from the date-time stamp.

Once the separate date and time values are available the data is pivoted around these two criteria to form a matrix of the power readings (Figure 4). For this project it was decided to perform this step at the beginning of the process in order to have all of the subsequent profiles created in this format, whereas if this step is performed at a later stage it would need to be performed multiple times to translate the data from the various profiles into this matrix format.



	A	B	C	D	E	F
1	s_datetime	hubid	power	n_1s_obs	n_1s_null	n_expected
2	01/10/2011 01:00	1	6167	59	0	60
3	01/10/2011 01:01	1	6282	60	0	60
4	01/10/2011 01:02	1	6269	60	0	60
5	01/10/2011 01:03	1	6294	60	0	60
6	01/10/2011 01:04	1	6287	60	0	60
7	01/10/2011 01:05	1	6299	60	0	60
8	01/10/2011 01:06	1	6297	60	0	60
9	01/10/2011 01:07	1	6310	60	0	60
10	01/10/2011 01:08	1	6309	60	0	60
11	01/10/2011 01:09	1	6292	60	0	60
12	01/10/2011 01:10	1	6280	60	0	60
13	01/10/2011 01:11	1	6307	60	0	60
14	01/10/2011 01:12	1	6312	60	0	60
15	01/10/2011 01:13	1	6312	60	0	60

	A	B	C	D
1	date time	date	time	power
2	01/10/2011 01:00	01/10/2011	01:00:00	104.5254
3	01/10/2011 01:01	01/10/2011	01:01:00	104.7
4	01/10/2011 01:02	01/10/2011	01:02:00	104.4833
5	01/10/2011 01:03	01/10/2011	01:03:00	104.9
6	01/10/2011 01:04	01/10/2011	01:04:00	104.7833
7	01/10/2011 01:05	01/10/2011	01:05:00	104.9833
8	01/10/2011 01:06	01/10/2011	01:06:00	104.95
9	01/10/2011 01:07	01/10/2011	01:07:00	105.1667
10	01/10/2011 01:08	01/10/2011	01:08:00	105.15
11	01/10/2011 01:09	01/10/2011	01:09:00	104.8667
12	01/10/2011 01:10	01/10/2011	01:10:00	104.6667
13	01/10/2011 01:11	01/10/2011	01:11:00	105.1167
14	01/10/2011 01:12	01/10/2011	01:12:00	105.2

	A	B	C	D	E	
21		01/10/2011	02/10/2011	03/10/2011	04/10/2011	05/
22	00:00:00	0	563.4833333	673.1833333	609.9166667	257
23	00:01:00	0	567	660.25	654.5166667	257.
24	00:02:00	0	565.0166667	644.7333333	698.6	170
25	00:03:00	0	568.0833333	637.0333333	762.3333333	
26	00:04:00	0	562.85	617.7833333	766.6333333	852.
27	00:05:00	0	564.8666667	696.7833333	788.45	808.
28	00:06:00	0	561.9833333	878	770.3666667	755.
29	00:07:00	0	562.3666667	904.6333333	757.25	
30	00:08:00	0	560.3833333	642.75	757.15	756.
31	00:09:00	0	603.2166667	684.8833333	756.1666667	816.
32	00:10:00	0	618.4	819.2333333	755.3833333	792.

Figure 4. Screenshots to show the initial data manipulation processes occurring during the algorithm. In particular showing the transformation of the dataset to a matrix format

3.3.3. Base Load

Once the power readings have been transformed into an appropriate format the disaggregation process can begin. Research into the field of load disaggregation suggested that a suitable starting point for many algorithms is to identify the base load, as this can be identified as the minimum power usage of a property and hence is straightforward to calculate, this is then assumed to be a constant throughout the day (Kilpatrick, et al., 2011).

There are two important points worth mentioning relating to the base load calculation in this project. The first is that the base load has been calculated separately for each day in the sample, since it was deemed possible that resident's behaviour may result in a fluctuating base load. For example if the users were to go on holiday for a week they may make a conscious decision to turn off appliances at the plug rather than leave them on standby, or perhaps during the trial they may purchase a new appliance which contributes to the base load, which would not have been present at the start of the trial period, hence the decision to calculate a variable base load.

The second consideration is related to problems with incomplete data. Although steps were taken to avoid using properties which had large sections of incomplete data, for some of the properties included in the sample there are still short periods where the data is incomplete, due to the malfunctions with the monitoring equipment. As a result, the decision was made to calculate the base load as the lowest non-zero power reading for each particular day. The main problem which manifests itself when calculating the base load in this project is when there is an interval prior to or directly after a period with no data, as these sometimes have a small number of the 1 second power readings contributing towards the average for that minute, hence making the average for that minute much lower than the true value. The base load algorithm may then pick this up as the base load as it could be the lowest non-zero but it may actually be lower than the real base load, so the base load profile is believed to be a slight underestimation of the actual base load.

In Excel a formula to calculate the lowest non-zero value in an array is:

*"=SMALL(**ARRAY**,COUNTIF(**ARRAY**,0)+1)"*

Throughout the algorithm there are additional stages to ensure that the sum of the disaggregated profiles which are created by the algorithm remain constrained at each 1 minute interval by the observed total value at that time interval, this is a property which has been built into the algorithm which was suggested in the literature (Akbari, 1995). For the base load profile, this is achieved by checking whether the suggested base load calculated by the lowest non-zero formula (above) is less than the observed value at that time interval and in any case where it is not, (i.e. when there is missing data) a zero is returned instead of the base load value. Once the base load profile has been created it is subtracted from the total demand profile to return an intermediate profile which in this project is called *total2*.

3.3.4. Heating Element Spikes

The next stage of the algorithm was to remove short duration high intensity spikes in electricity demand which are typically associated with heating elements such as kettles, toasters, hobs and electric showers (Kilpatrick, et al., 2011). According to sources in the literature, the next stage would normally have been to remove the cold cycle profile (Kilpatrick, et al., 2011) and this strategy was tested. However, due to the mechanism which was used to extract the cold profile in this project, improved cold cycling results were observed by first removing the heating element spikes and then removing the cold cycle in the following step. This is due to the significant impact that intense spikes in demand have on the running averages which are used to predict the cold cycle profile and hence removing the spikes first allows the cold cycle running averages to be calculated from a more stable baseline.

There were two methods which were tested for the removal of the heating element spikes. The first was to consider each time interval and compare the value observed from the *total2* profile at that time to the mean of the 10 cells before and 10 cells after the interval of interest, then if the difference is larger than a threshold value, usually 500 W, then the value is assumed to be part of a spike and is included in the heating element profile as the difference between the interval of interest and the average of the surrounding cells. This comparison is then applied to each interval in the trial period in order to build up a heating element profile. Whilst this method works well for short duration spikes, for example a kettle running for 1 or 2 minutes, it becomes gradually less effective as the duration of the spike increases, for example when an electric shower is in operation for more than 11 minutes consecutively. This is due to the fact that during an extended spike, the intervals which are used for the comparative average are also elevated values which makes it difficult for the algorithm to identify whether the threshold has been met. Also, it is possible that the amplitude of the central values of the spikes are underestimated as they are compared to averages which contain more spike elevated values.

In order to avoid this issue, the solution used in this project was to create a range of filters for various different spike durations. In each filter the 1 minute interval of interest is compared to the two unique intervals on either side of the interval of interest which become progressively far from the interval of interest. For example the first filter which tests for a 1 minute spike compares the value of the interval of interest to the average of the two values of the cells which are directly adjacent to the interval of interest. The 3 minute filter then checks the interval of interest to the average of the two values of the cells which are two cells away from the interval of interest. This process is then repeated up to intervals of 23 minutes. Examples of the first 3 filters are shown below, these represent the formulas to calculate the 1, 3 and 5 minute spike profiles:

“=IF(**CELL-((CELL-1** + **CELL+1)**/2)>**THRESHOLD VALUE**, **CELL-((CELL-1** + **CELL+1)**/2),0)”

“=IF(**CELL-((CELL-2** + **CELL+2)**/2)>**THRESHOLD VALUE**, **CELL-((CELL-2** + **CELL+2)**/2),0)”

“=IF(**CELL-((CELL-3** + **CELL+3)**/2)>**THRESHOLD VALUE**, **CELL-((CELL-3** + **CELL+3)**/2),0)”

The value for the amplitude of a spike at any given interval is then chosen as the maximum of the various different spike filters for that interval. The benefit of this method is that it ensures that even for wider spikes the entire spike amplitude is being included in the heating element profile.

The decision to include spikes of up to 23 minute was to ensure that even in periods with highly volatile electricity usage, the maximum possible number of spikes were being included in the heating element profile. It was also considered that possible problems associated with including too many features as heating element spikes could be avoided by setting an appropriately high threshold value.

In most instances the threshold value which was used to determine whether or not to include an interval as a spike was 500 W. This value was selected as it ensured that on either side of an event involving a heating element the majority of the spike duration was included in the heating element profile. Take the example of a kettle which is switched on for 1 minute with a continuous power usage of 2 kW. If the 1 minute duration occurs so that the first 15 seconds of usage are in one aggregated one minute interval and the remaining 45 seconds are in the following one minute interval then the 2 kW spike would actually appear as a 2 minute spike of 500 W for 1 minute followed by 1,500 W for 1 minute (Figure 5). Hence the decision was made to allow spikes as low as 500 W to be included in the heating element profile.

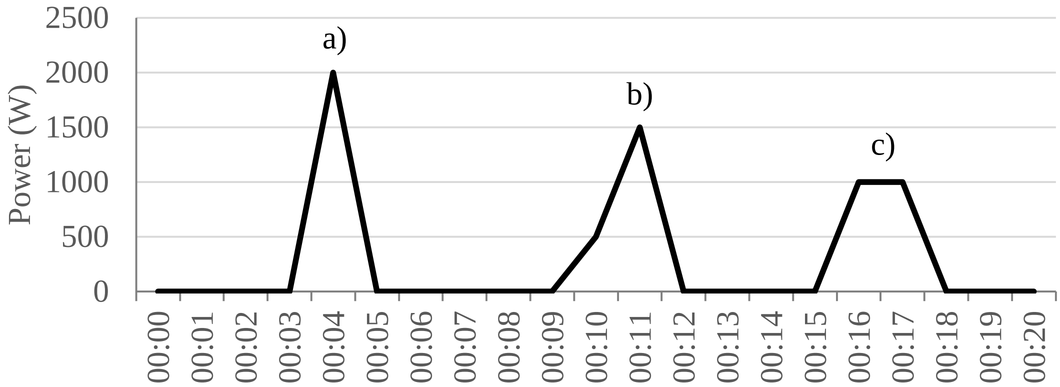


Figure 5. Hypothetical example of heating element spike using artificial data. In this example three identical spikes in terms of intensity (2 kW) and duration (60 seconds) are shown as they would appear in the aggregated data if a) all 60 seconds of activity fell within the same 1-minute interval, b) the first 15 seconds of activity appeared in one interval and the remaining 45 appeared in the consecutive interval and c) the 60 seconds of activity bridged the two aggregated intervals evenly.

In a small number of properties it was necessary to make an exception and increase the threshold value. This happened in instances where the cold cycling magnitude was particularly high (greater than 500 W) and the duration of the ON cycle was shorter than 20 minutes, which meant that cold cycling features were being picked up as heating element spikes.

Once the heating element profile was created it was subtracted from *total2* to create a new intermediate profile called *total3*. Again measures were included to ensure that the resultant sum of disaggregated profiles would be constrained by the observed total profile.

3.3.5. Electric Showers

Heating element spikes associated with electric showers were of particular interest to this project due to their large power usage and relatively long duration, making them good candidates for peak demand reduction interventions. With this in mind an additional filter was applied to the heating element profile. Since electric showers are unique in that they have a power requirement of over 7 kW (Walker, 2009), it was assumed that any spikes over 6 kW were associated with electric showers (in order to account for the peak reduction effects associated with aggregation described previously in Figure 5). So two new profiles were created which separated all heating element spikes over 6 kW from those below 6 kW and created an electric shower profile and a separate residual heating element profile.

3.3.6. Cold Appliances

The next stage in the algorithm is to create and subtract the cold appliance profile. The most suitable method for generating a cold appliance profile was based on comparing running averages. This stage in the process is the most manual of the different components of the algorithm since it requires the input of three factors which need to be manually determined from the data set, these three factors can be determined by observing a period of stable electricity usage, for example over night when appliances are not being switched on and off. Figure 6 below, which consists of manufactured data, shows the three parameters which need to be determined in order to express the cold cycle of an appliance. These are the length of time an appliance is on, the length of time an appliance is off and the power usage of the appliance when it is on.

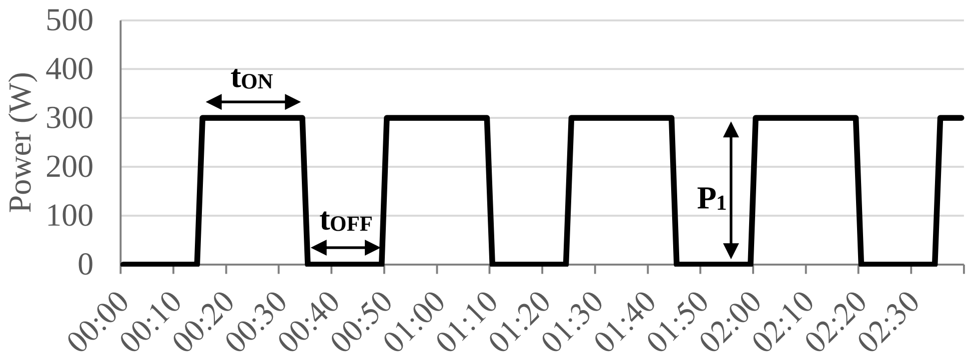


Figure 6. Representative example of a cold appliance cycle using artificial data. In order to show the important parameters used to characterise a cold cycle

A number of methods were considered when determining which moving average to use for the cold cycle element of the algorithm. The first was to estimate the total length of a cycle (i.e. from ON and back to ON again) and then divide the time into two even segments and the other two methods were to make the lengths of the period an average was calculated over correspond to the length of the on or off cycle. Both variations, i.e. on first and off first were tested. For an example cycle where the appliance is on for 20 minutes and off for 40 minutes the following average comparisons were tested, to identify an optimal match.

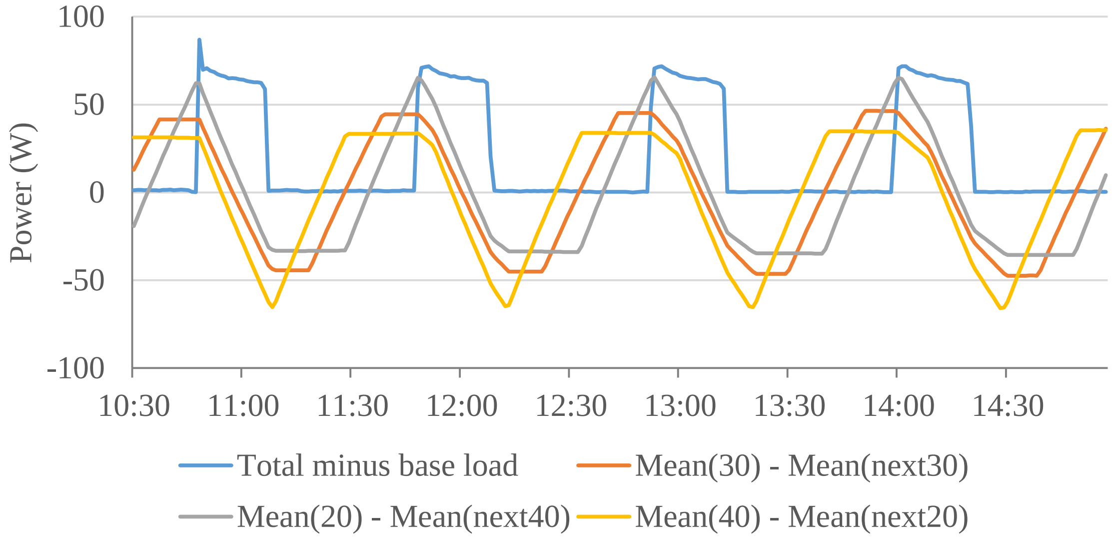


Figure 7. Graph to show the various running averages which were considered for the cold cycling stage of the algorithm

Based on the observations from this analysis it was decided that the best comparison of averages to use to determine whether a cold cycle was on or off was based on the comparison of an average of the number of cells that would make up a typical ON period minus the average of the consecutive number of cells which would characterise an OFF period, as this provided the most obvious gradient difference when the cycle is ON compared to when it is OFF. The next stage of the cold cycling algorithm is to determine whether the gradient of the trend is negative. This is simply done by subtracting the value of the moving average for the following cell from the current cell. If the value is below a specified negative threshold then the cycle is deemed to be ON and is given the value of the power usage for that appliance in the cold cycle profile.

Similarly to the other stages in the algorithm measures were taken to ensure that the value obtained for the cold cycle profile could not exceed the remaining *total3* value for that specific time interval in order to ensure that the sum of the disaggregated profiles is constrained by the total electrical demand reading at all times.

In some properties there are multiple cold cycles present. In this instance the same process is repeated twice with different parameters corresponding to each of the observed cold appliances. The first profile to be removed is the profile with the shortest overall cycle length. Once this has been removed the same process is repeated for an intermediate total profile using the parameters for the longer cycle. This creates a total cold cycle profile which represents the overall cold cycling picture. The resultant profile is the uncharacterised portion of the profile.

3.3.7. Lighting

In order to demonstrate proof of concept, a lighting algorithm was developed which was capable to a certain extent of determining the proportion of the total load profile which is attributable to domestic lighting. The strategy used for this stage of the analysis varies significantly from the initial stages of the algorithm which are described above, in that it requires a secondary dataset and that it is based on differences in the load profile between summer and winter, rather than short term patterns in the data. The additional dataset which is used for this stage is another 28 day period of 1-minute power readings for the same properties for the period from 1st June to the 28th June 2011 (the dataset discussed previously runs from the 1st October to the 28th October 2011). Due to time constraints and the large amounts of manual processing required, it was only possible to run this stage of the analysis on a subset of the properties. The properties included in the lighting analysis are shown in Appendix A.

The basic premise of this analysis is to compare the uncharacterised profile of each property in June against October, between the median sunset times of the 2 months, i.e. 18:15 for October and 21:21 in June (United Kingdom Hydrographic Office, 2014). Since it is assumed that a significant proportion of the difference in the uncharacterised loads for these 2 months would be associated with lighting. However the author does also acknowledge that other appliances, particularly tumble dryers, may be used more during this time in the winter period which would overestimate the lighting profile identified by this analysis.

The first step in this analysis is to run the previously described algorithms for each of the months, in order to generate profiles which have had heating elements, base loads, cold appliances and electric showers removed. The next step is to subtract the June uncharacterised profile from the October uncharacterised profile between the median sunset times.

The profile generated by this method only considers the period from 18:15 to 21:21 and hence it is not sufficient to identify the total electricity usage reduction which could be achieved by interventions affecting lighting. However it does cover peak times and hence the method is deemed sufficient for the purposes of this project.

Survey data which is available for most of the properties in the sample, was then used to identify the proportion of fittings in each dwelling which use low energy bulbs. This data was then used to model the potential reduction in energy used for lighting that could be achieved in each property if all bulbs were to be replaced with low energy bulbs.

3.3.8. Uncharacterised

Following the extraction of profiles for all the appliance types described above, the remaining electricity usage is grouped into a final uncharacterised profile. This profile makes up the difference between the sum of the appliance type profiles and the total observed profile. This profile is expected to include a range of appliances such as televisions, personal electronics, computing and wet appliances such as washing machines and dishwashers.

3.4. Analysis

3.4.1. Appliance Load Profiles

Once the individual appliance type profiles had been disaggregated at the individual household level a variety of analyses were conducted.

Firstly, ‘typical’ profiles for each of the load types for a particular property were generated by averaging the power usage at each time interval during a day across all of the days in the trial period. For each load type standard deviations for different time intervals have also been calculated in order to identify the variation that are observed for that load at a particular time from day to day.

Further analysis involved aggregating each of the load types across a range of different properties in the sample and a range of different days in order to identify more generally the typical load profile for that particular appliance, along with the standard deviations which provide an idea of how that load varies from day to day. Each of the appliance load profiles is generated based on data from 51 properties each with 28 days of data available, hence providing a total sample of 1,428 individual days ensuring statistical significance of the appliance profiles which have been generated.

By combining those loads it was possible to identify how significant a role each load plays in the overall load profile for the total of all the properties in the sample

3.4.2. Peak Load Reductions

Once the total load profile was successfully disaggregated into component parts, various elements of the profile were modelled assuming they had undergone a particular intervention.

The first of these interventions was to assume that all standard bulbs in each property were replaced with low energy equivalents. Survey data gathered by the energy and communities project provided information on the proportion of standard light bulbs in each of the properties. The observed profile was then scaled for each property to reduce the power usage of the standard bulb proportion by 80%, in order to simulate replacing these bulbs with low energy bulbs which use 80% less energy (Energy Saving Trust, 2014b).

The next analysis aimed to simulate the impact of an intervention to switch off cold appliances during the peak time. This was achieved by setting the power usage of cold appliances to zero during the peak period. Since there was uncertainty as to the extent of a power surge which may be experienced once the appliances were allowed to be turned back on, modelling was also performed which reallocated the saved energy from peak to the period following peak.

The final intervention which was considered was focused on electric showers. The modelling involved shifting all shower events which were observed during the peak period into the period following peak, in order to simulate the impact of prohibiting residents from using electric showers during peak.

4. Results

4.1. Introduction to Results

The results chapter of this report is split into two main sections in order to address the two key challenges of this project individually. The first section focuses on a qualitative assessment of how successfully the algorithm was able to disaggregate domestic load profiles into individual appliance type profiles. The chapter then moves on to the results of this project in terms of the identified 'typical' appliance load profiles and the possible reductions to the total load profile which may be achieved by interventions targeting these appliances.

4.2. Appraisal of the Algorithm

4.2.1. Base Load

As described in the methodology section of this report, base load profiles were calculated by taking the minimum non-zero value of the power readings for each property for each day and subtracting that value as a constant throughout the respective day.

This method has proved to be successful for days where the dataset is complete, however the method is less successful on days which have missing data as shown by the example below in Figure 8 and Figure 9. Figure 8 shows that there were 2 days in October 2011 where house 001 had incomplete data, these were the 8th and 26th. Days of incomplete data are characterised as days where the total load profile drops to zero. Since this would imply absolutely no appliances were switched on, a much more likely cause for null values is a malfunction with the monitoring equipment.

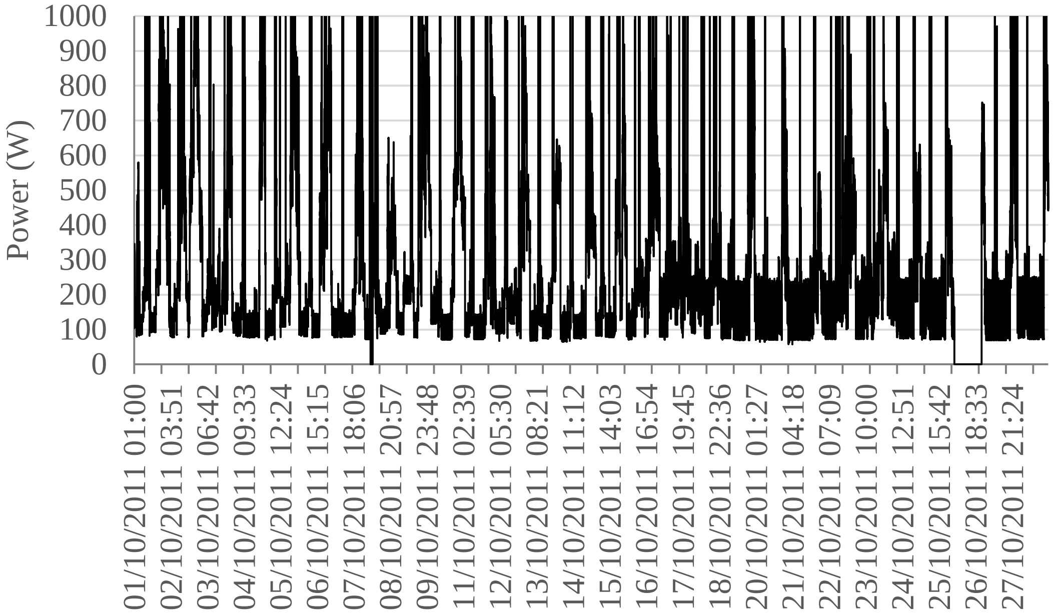


Figure 8. Recorded power consumption of house 001 from 1st - 28th October 2011 at 1 minute intervals. Axis maximum of 1000 W has been chosen to highlight base load data which has led to peaks being truncated

Figure 9 shows the base load value that the algorithm has allocated to house 001 for each day in the month. It is clear that for days which have missing data, the algorithm will sometimes provide an erroneous base load value which is below the real base load value for that day, as shown by the base load results for the 26th. However, when the dataset is complete for an entire day then the algorithm does a good job up picking up the actual base load, as demonstrated throughout the rest of the month.

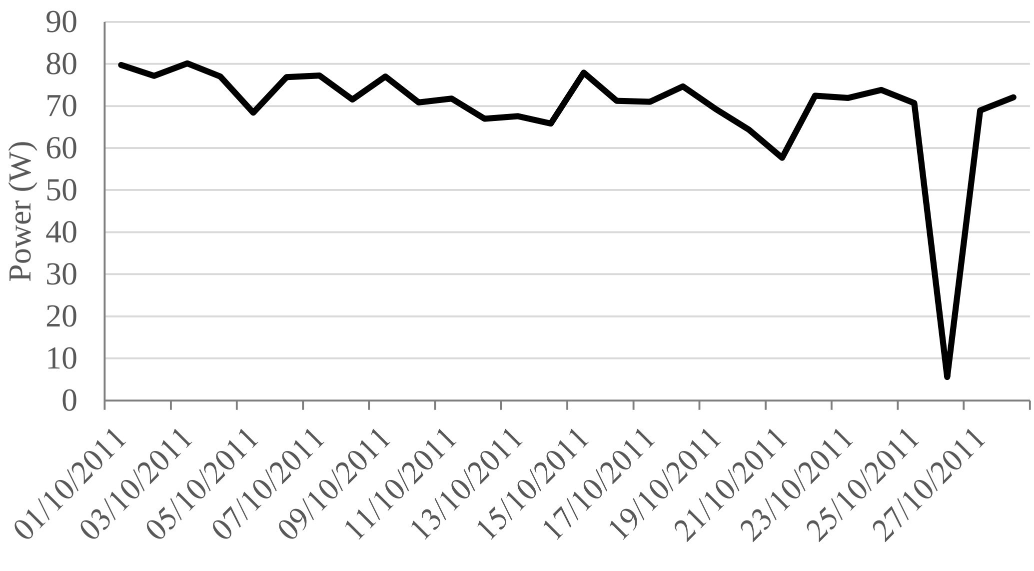


Figure 9. Base load power consumption identified by the algorithm for daily intervals from 1st - 28th October 2011

For the 8th October 2011 which also has incomplete data, closer observation of the load profile around the periods of missing data explains why the algorithm still successfully identified the base load. As shown by Figure 10, the surrounding values to instances of missing data were already elevated substantially above the expected base load (typically above 200 W for this period whereas the base load for this house is expected to be around 80 W). Hence even if some null values were included in the average for an adjacent time interval (which would lower the average) in this instance it has not resulted in a smaller value than the actual base load.

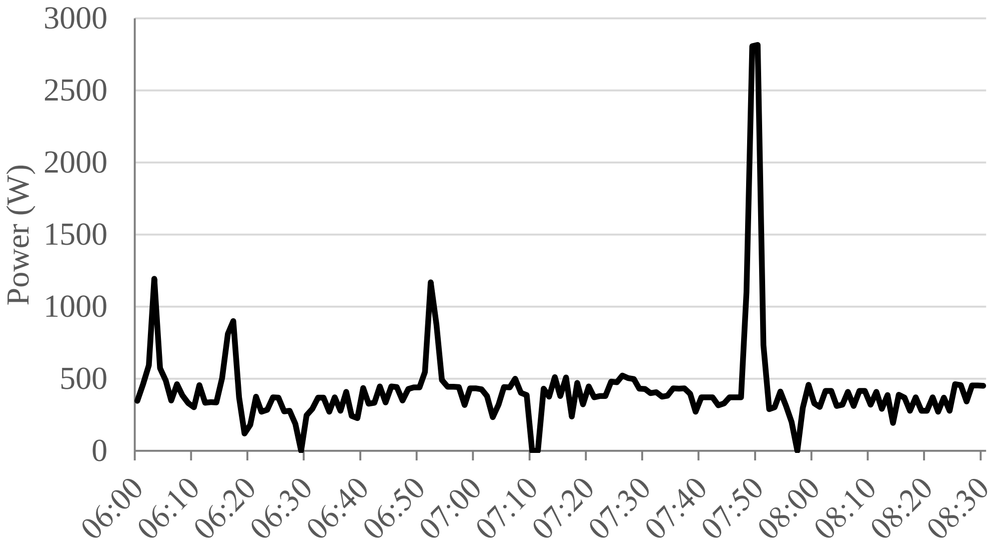


Figure 10. Power consumption for house 001 on the 8th Oct 2011 between 06:00 and 08:30

In summary, the algorithm for identifying the base load works well and the process is relatively straight forward, as shown by the successful results throughout most of the example above. The main problem which can occur is that the base load can occasionally underestimate the magnitude of the base load, if the data set is incomplete for a particular day.

4.2.2. Heating Elements

The algorithm used to remove the spikes associated with heating elements works well when peaks appear during a period of stable electricity usage, as shown by the peaks at 08:38 and 18:03 in Figure 11 below. In these instances the algorithm is able to almost perfectly identify the entire duration and magnitude of the peak and return a smoothed profile for the remaining electricity usage.

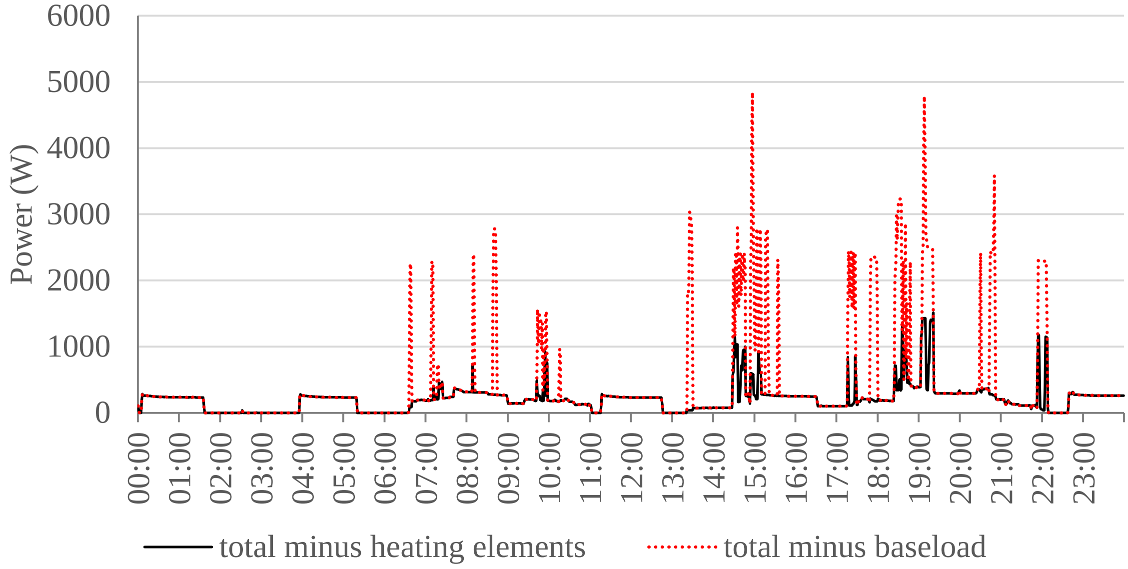


Figure 11. Power consumption data from house 022 for the 21st October 2011. Where total minus base load represents the total profile with the base load for that day subtracted and total minus heating elements represents the total profile minus the base load and minus the heating element profile.

It continues to work relatively successfully even when there are large numbers of peaks adjacent to one another, for example during the period between 14:28 and 15:34 (Figure 11) and between 16:45 and 18:40 (Figure 12).

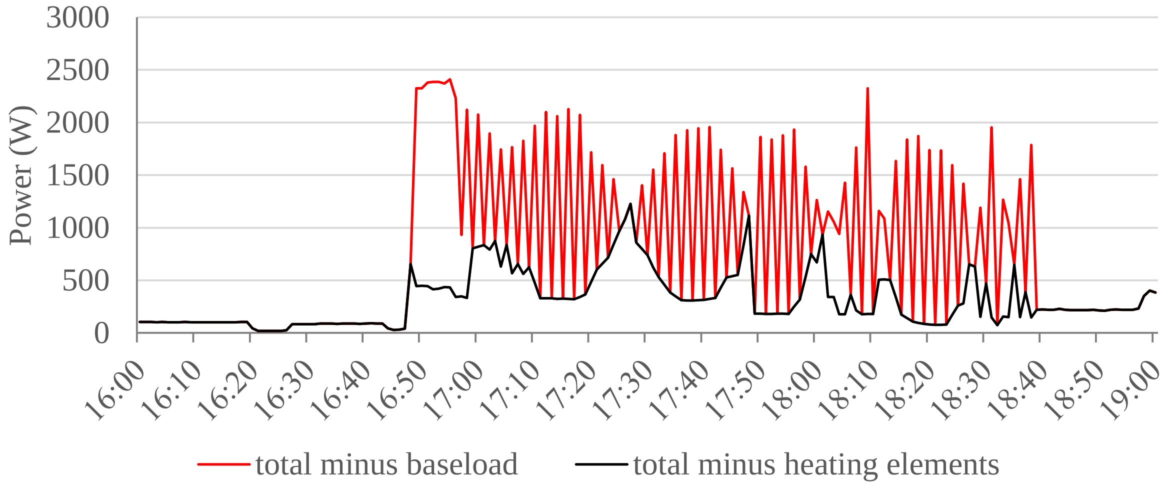


Figure 12. Power consumption data from house 008 for the 8th October 2011. Where total minus base load represents the total profile with the base load for that day subtracted and total minus heating elements represents the total profile minus the base load and minus the heating element profile.

There are however a number of issues with the output of the algorithm. The first occurs when there are peaks with a value below 500 W (the peak threshold) at the beginning or end of the peak. These are caused due to the aggregation and averaging of the load profile to 1 minute intervals. An example of this feature is observed at 08:09 in Figure 11 and can be seen as a short spike in the profile even once the data has had peaks removed.

The second which can be seen to occur in the above load profile (Figure 11) between 21:53 and 22:08 is the result of the selection of the widths of the peaks of interest. Since the algorithm looks at a maximum width of 23 cells, whenever a peak lasts for longer than 11 minutes then the peaks on the end will only ever be recorded as half the magnitude, since the algorithm is working on the average of a non-peak against a peak value. However 11 minutes is still longer than peaks which have typically been extracted in the literature (Kilpatrick, et al., 2011).

4.2.3. Electric Showers

The electric shower profile generated by the algorithm is created based on the modelled heating element profile. Since the heating element algorithm has already been identified as working relatively successfully, this provides a strong foundation for the electric shower profile.

In order to validate the results of the electric shower algorithm, one dwelling which presents the characteristics of an electric shower was analysed. This was done by characterising each of the modelled electric shower events identified by the algorithm and creating a frequency distribution of the duration of the events and magnitude of the events (in terms of power usage). The chosen property for this analysis was house 108, for which 45 electric shower events were identified during the period of the 1st to the 28th October 2011.

The first of the characteristics to check was the magnitude of the spikes which had been identified by the algorithm. Encouragingly, this analysis found that 29 of the 45 events had a magnitude between 7700 and 8100 W (mean of 7880 W and standard deviation 439 W), all 45 events were within a range of 2500 W (6400 W – 8900 W) and the events were relatively normally distributed, as shown by Figure 13 below. This suggests that the algorithm is accurately picking out appropriately sized peaks.

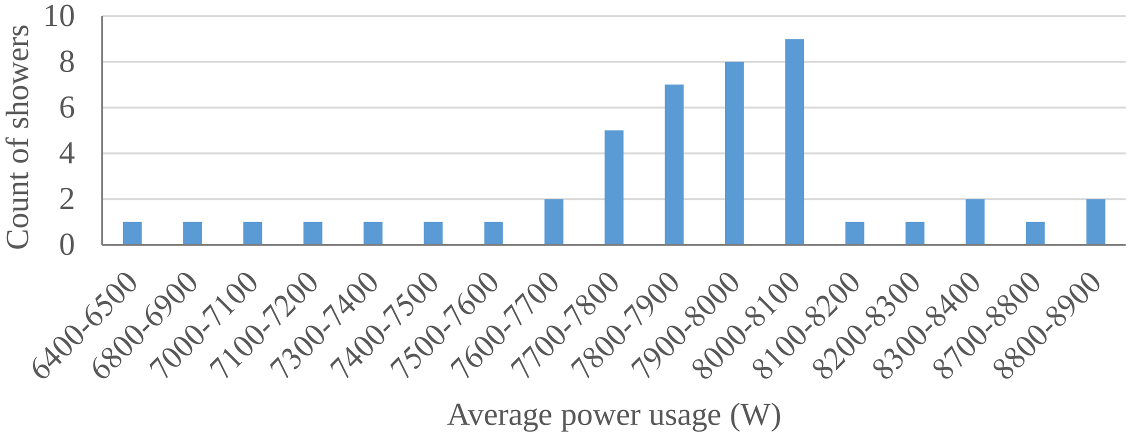


Figure 13. Distribution of the power consumption of electric shower events observed by the algorithm for 1st - 28th October 2011 in house 108

The next characteristic of the electric shower peaks which was analysed was the duration of the events. Similarly to the magnitude of the events, this analysis found the duration of the events to be approximately normally distributed with a mean event duration of 5.4 minutes and standard deviation of 2.4 minutes. The frequency distribution of event durations is shown below in Figure 14. The results of the event duration analysis suggest the events identified by the algorithm are likely to be representative of the actual showers taken by the residents of house 108.

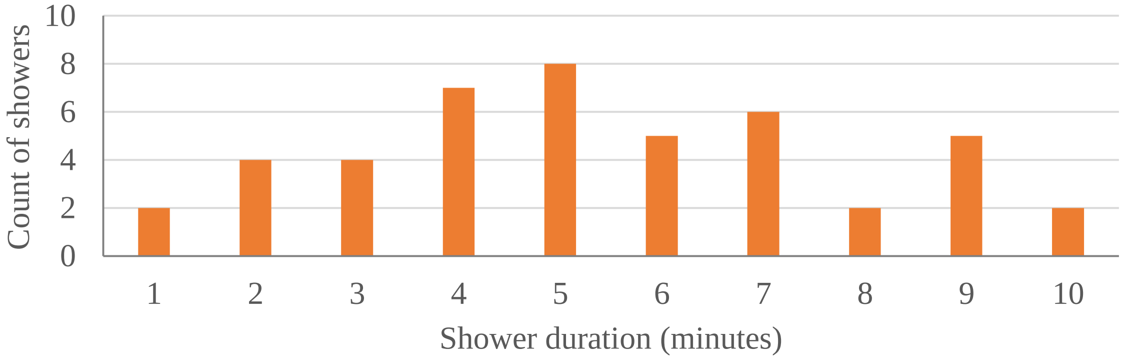


Figure 14. Distribution of the duration of electric shower events observed by the algorithm for 1st - 28th October 2011 in house 108

The combination of the analysis of event duration and event magnitude suggest that the electric shower profile created by the algorithm is realistic and serves to validate the algorithm.

Whilst it is believed that the algorithm generally works well, there are occasionally slightly higher shower peaks than the expected shower peak for that dwelling. It is believed this could occur when the shower peak overlaps with another short duration appliances which gets included in the peak profile. In further versions of the algorithm this could be avoided by adding a narrow minimum and maximum value for the shower peaks.

With respect to event duration, events are never found to be unreasonably longer than the mean duration, however the two particularly short events of just one minute are acknowledged as being suspicious and it is postulated that these could be the result of a number of high power consuming appliances running simultaneously. For example tumble dryers which typically have power consumptions in the range of 2 – 4 kW and cycle lengths of 1 – 2 hours alongside cooking appliances (Appendix B) (DSG Retail, 2014a; DSG Retail, 2014b; DSG Retail, 2014c; DSG Retail, 2014d).

4.2.4. Cold Appliances

Of the various appliance type profiles which needed to be extracted from the overall load profile, cold appliances proved the most challenging to successfully extract. This was due to inconsistencies in cold cycle parameters throughout the dataset.

The method which was selected to perform the task of extracting the cold appliance profiles works well when identifying cold appliances during periods of stable overall electricity usage, such as overnight or during weekday afternoons when residents are not present. This can be observed in the load profile shown below in Figure 15. Once the cold appliance profile which has been determined by the algorithm has been subtracted from the overall profile, the result is a smoothed load profile with most cold features successfully removed. The first 4 ON cycles are reasonably successfully removed and result in a relatively stable auxiliary appliance profile as shown in black, with only slight spikes observed at the beginning of some of the ON periods.

A number of issues arise when the cold cycle algorithm runs in times of inconsistent electricity usage. The first which is also observed in Figure 15, is that the algorithm tends to elongate the ON period of the cycle in the lead up to a general rise in electricity usage for example during the last cycle before residents wake up or return from work. This is observed between 04:46 and 05:58 during the cycle below (Figure 15), where the algorithm is allocating non-cold appliance electricity consumption to the cold profile. In this profile there is also a period between 07:11 and 07:33 for which the algorithm has incorrectly assumed the cold cycle should be ON.

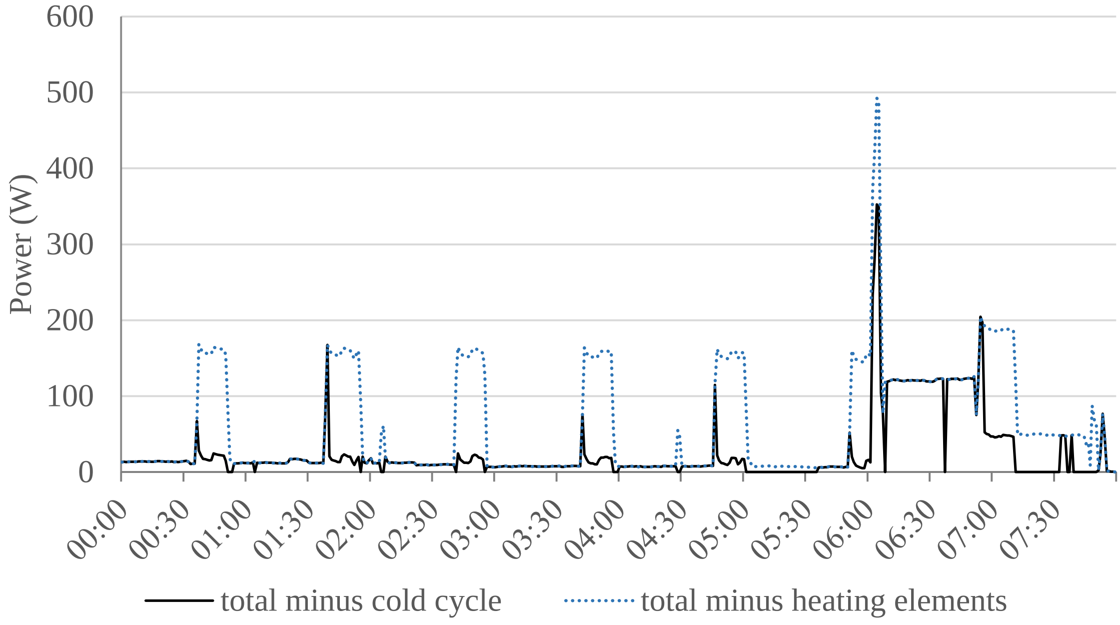


Figure 15. Power consumption data from house 026 for the 8th October 2011 between 00:00 and 08:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles.

For certain dwellings in the sample multiple cold cycles were observed. In these instances a two stage cold appliance algorithm was applied to the data. As the complexity of the cycling increased, it became more difficult for the algorithm to accurately identify the two cold cycles (Figure 16). Whilst the algorithm can still work effectively in identifying the location of the cold appliances being active, it leaves more noise than when an individual algorithm runs.

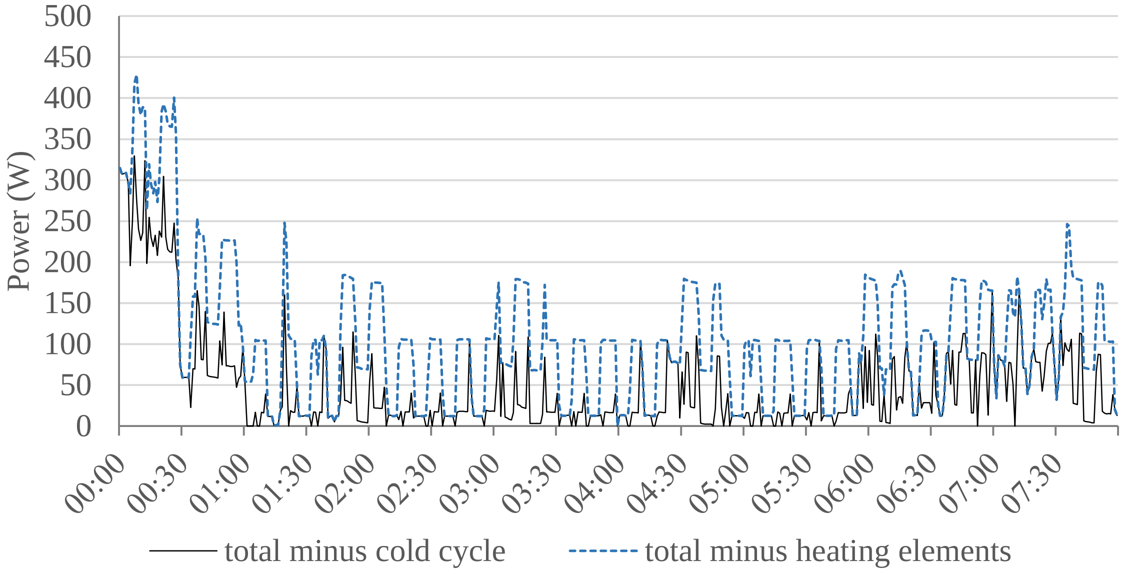


Figure 16. Power consumption data from house 001 for the 21st October 2011 between 00:00 and 08:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and the two component cold cycling profiles.

There are two main circumstances which cause the algorithm to work less successfully. The first is when the total profile is more unstable such as when residents are home and awake, particularly during weekday evenings. Figure 17 shows the electricity usage from house 119 on the 16th from 1600 to 2400 and demonstrates how an unstable electricity usage has a significant impact on the accuracy of the cold cycle algorithm. Due to the large variation in electricity usage, the subsequent cold appliance profile which was generated shows much more rapid changes in cold cycling than would be anticipated.

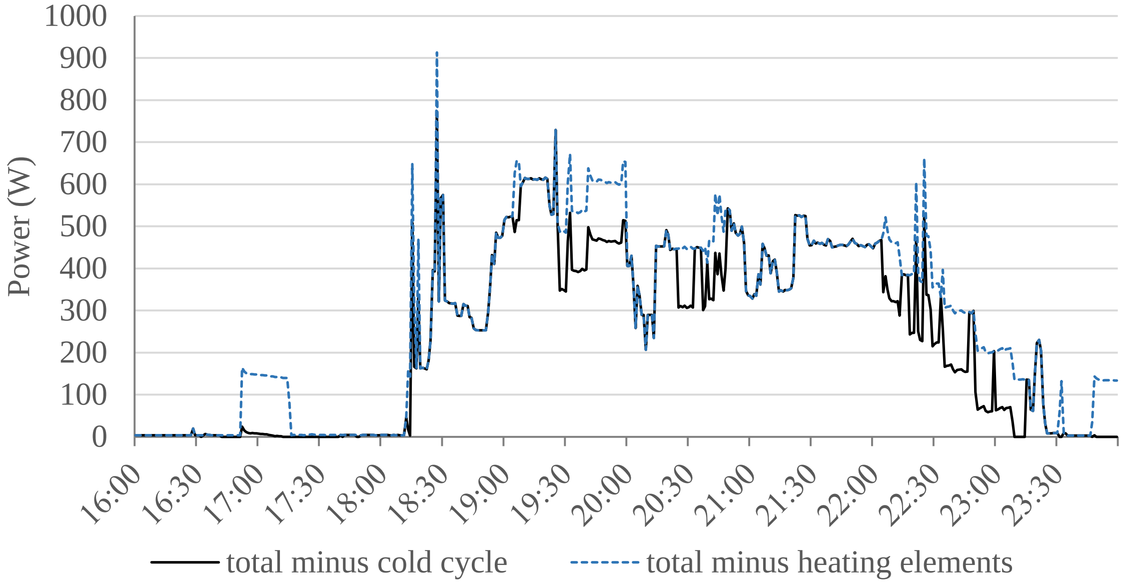


Figure 17. Power consumption data from house 119 for the 16th October 2011 between 16:00 and 23:59. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles.

The second major challenge for the algorithm is when the compressor of the fridge or freezer is required to run for longer during an individual cycle (for example when ambient temperature goods are placed into the freezer) or the compressor does not use a constant power. The cold cycling profile for house 029 on the 10th between 0000-1000 shown in Figure 18, demonstrates the difficulties faced by this algorithm when the length of the ON cycle varies from one cycle to the next. Figure 18 shows that the duration of the modelled ON period of the cold cycle remains relatively constant, despite the length of the observed ON period varying slightly. The modelled ON period tends to be present from the end of the observed ON cycle and it is the beginning which is occasionally missed out from the modelled profile.

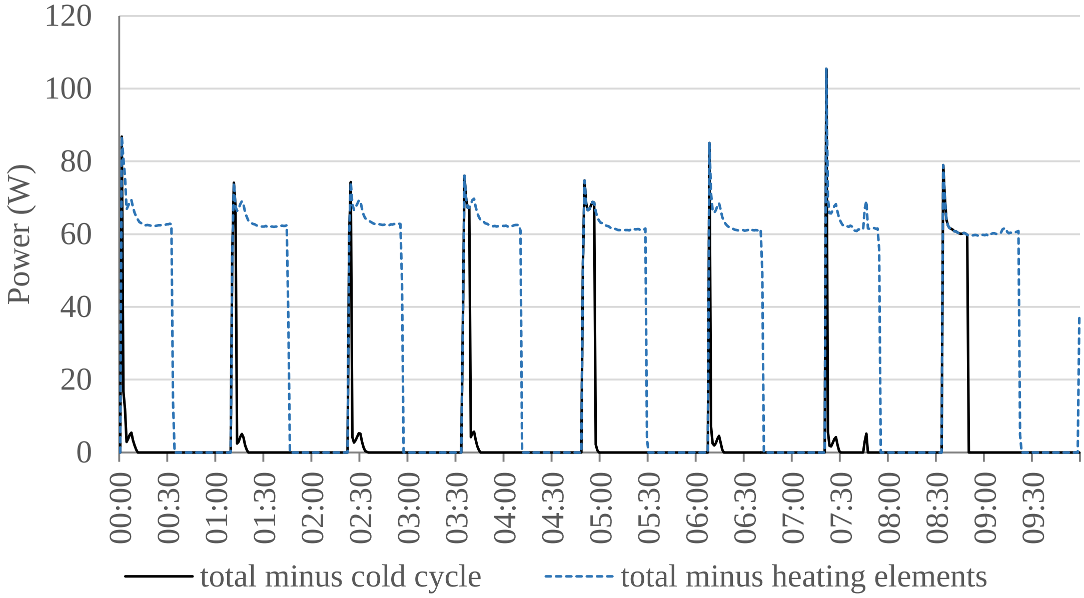


Figure 18. Power consumption data from house 029 for the 10th October 2011 between 00:00 and 10:00. Where total minus heating elements represents the total profile minus the base load and minus the heating element profile and total minus cold cycle represents the total profile minus the base load, heating element and cold cycling profiles.

4.2.5. Lighting

The lighting analysis conducted in this report was implemented according to the details given in the methodology section. This involved comparing the winter (October) uncharacterised load profile against a summer (June) uncharacterised load profile. For the purposes of this project the difference was only considered between the median sunset time in October (18:15) and the median sunset time in June (21:21), however there are interesting characteristics which occur out of this time frame which are also discussed in this section.

Due to time constraints it was not possible to perform this analysis on each of the 51 properties in the overall sample, so in order to prove the potential of the method, a subset of 10 properties from the sample were selected, these are listed in Appendix A. Due to the smaller sample size, all findings relating to lighting should be considered carefully and are given subject to greater levels of uncertainty than other appliance type profiles discussed in this report. Despite the small sample size, the initial results gathered from this analysis are promising and serve to demonstrate that this avenue could be explored further.

The profiles shown in Figure 19 below represent the October mean profile, June mean profile and the difference between the two, for house 015 between 17:00 and 23:59. The two vertical dashed lines represent the median October sun set time and median June sun set time, on the left and right hand sides respectively. This profile shows that the mean uncharacterised profiles of both time frames are similar up until around 18:00, at which point they begin to diverge until around 22:00 where the converge again. The times where these two profiles diverge corresponds directly with the time of day when it would be dark in October but still light in June. In part this is believed to be the result of lighting which is in use during the October period and hence the difference can be an indicator of the domestic lighting load of a property in October between these times.

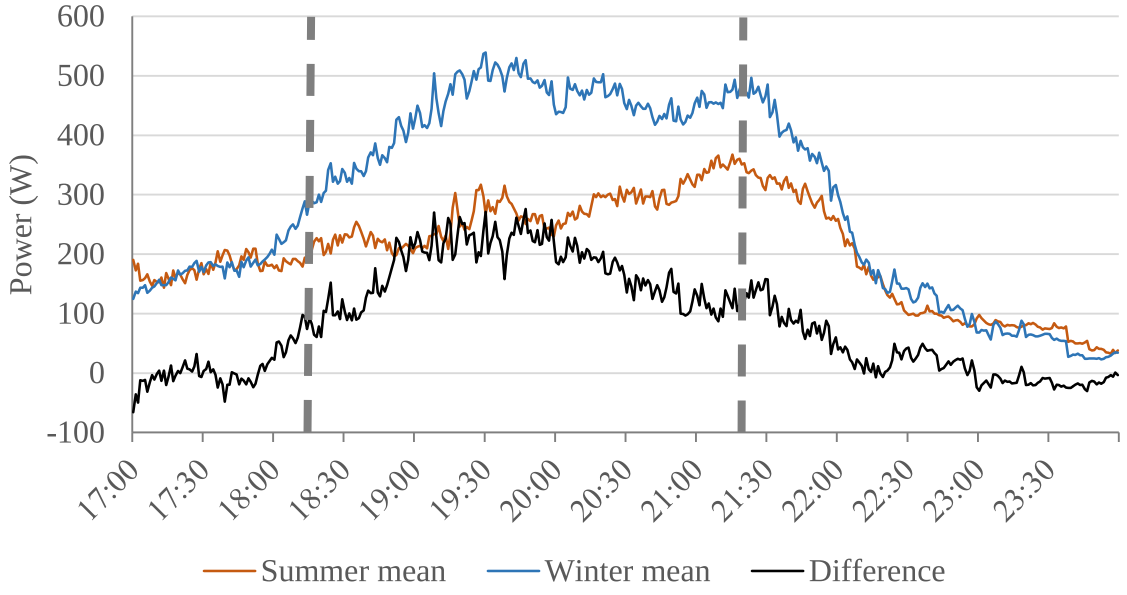


Figure 19. Average power consumption profiles of uncharacterised appliances for house 015 from the 1st – 28th October 2011 and 1st – 28th June 2011 between 17:00 and 23:59. Here the Difference plot represents the assumed lighting load profile for this property in October. From left to right the vertical dashed lines represent median sunset in October and median sunset in June

Whilst peak demand falls within the times discussed in the previous example, the morning peak is another period of the day for which this analysis may also provide useful results, as shown by Figure 20 below. From left to right, the vertical dashed lines in Figure 20 represent median sunrise in June, median sun rise in October, median sun set in October and median sun set in June. Again from this graph the efficacy of the analysis during the evening can be observed. It is also possible to estimate how much of the morning peak (06:00 – 09:00) is due to lighting, since it is anticipated that there would be no lighting load during that time in June as the sun has already risen, whereas this period begins in the darkness for October and hence the difference could represent the lighting load.

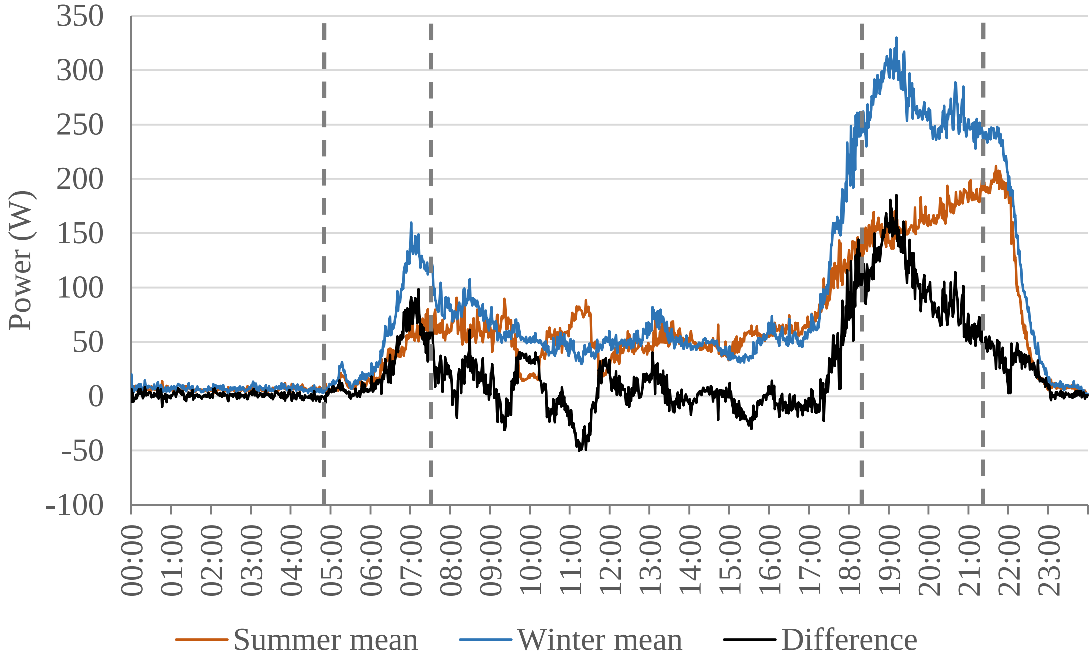


Figure 20. Average power consumption profiles of uncharacterised appliances for house 014 from the 1st – 28th October 2011 and 1st – 28th June 2011. Here the Difference plot represents the assumed lighting load profile for this property. From left to right the vertical dashed lines represent median sunset in October and median sunset in June

Based on qualitative observation of the profiles shown in Figure 19 and Figure 20, the lighting analysis seems to provide intuitively reasonable results given the relative simplicity of the method. The main drawback of this method is that it only identifies the load when data which would not have a lighting load is available. It also does not consider the fact that there may be other differences between the loads for winter and summer, such as more general behavioural differences. For instance the increased likelihood of households using a tumble dryer in winter, due to the difference in weather conditions.

4.2.6. Edge effects

A number of the stages in the algorithm work based on calculating running averages. Since the running averages are calculated based on empty cells at the beginning and end of the dataset for each day, a number of 'edge effects' are observed in the resultant load profiles for the disaggregated loads.

The first of the edge effects is observed in the heating elements profile. At the beginning of the day it was necessary to only allow each iteration of the heating element algorithm to work once there were sufficient populated cells prior to the interval of interest, as the algorithm looks at cells on both sides of the cell under investigation. Hence an effect is observed whereby there is a gradual rise in power associated with heating elements from zero to the correct value around 12 minutes in, as shown in Figure 21 below.

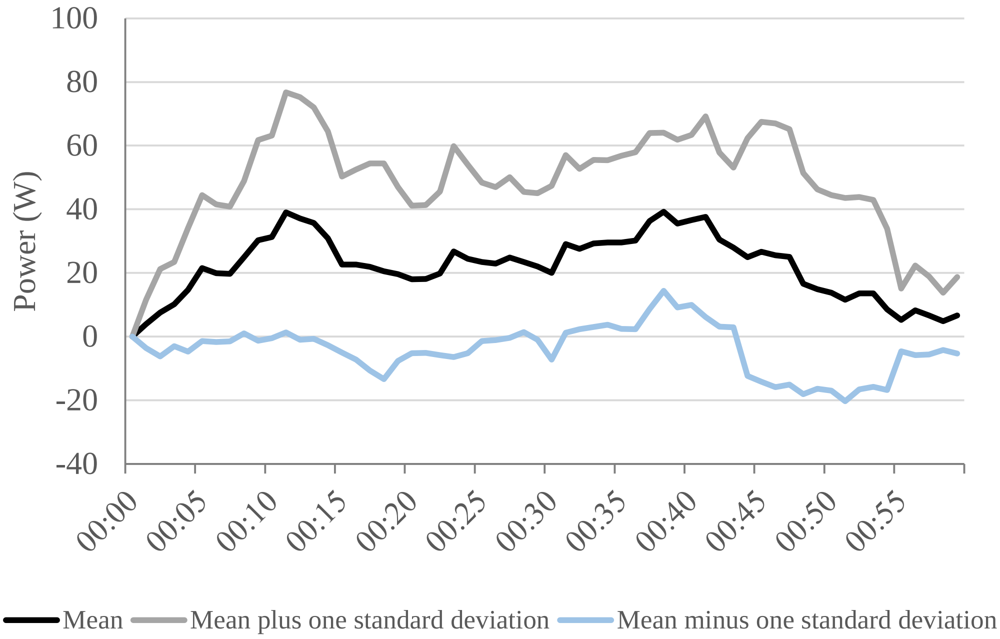


Figure 21. Graph showing the heating element profile and associated standard deviation margins between 00:00 and 00:59 demonstrating edge effects observed in the heating element profile

The second appliance type profile which was affected by 'edge effects' associated with the design of the algorithm was the cold appliance profile which encountered edge effects at both the beginning and end of the day.

There is one step in cold appliance profiling algorithm which required data from the previous interval to be considered. Since this cannot be achieved in the first cell, it was necessary to force the first cell to adopt a null value for the first minute interval at the beginning of the day, as demonstrated by Figure 22.

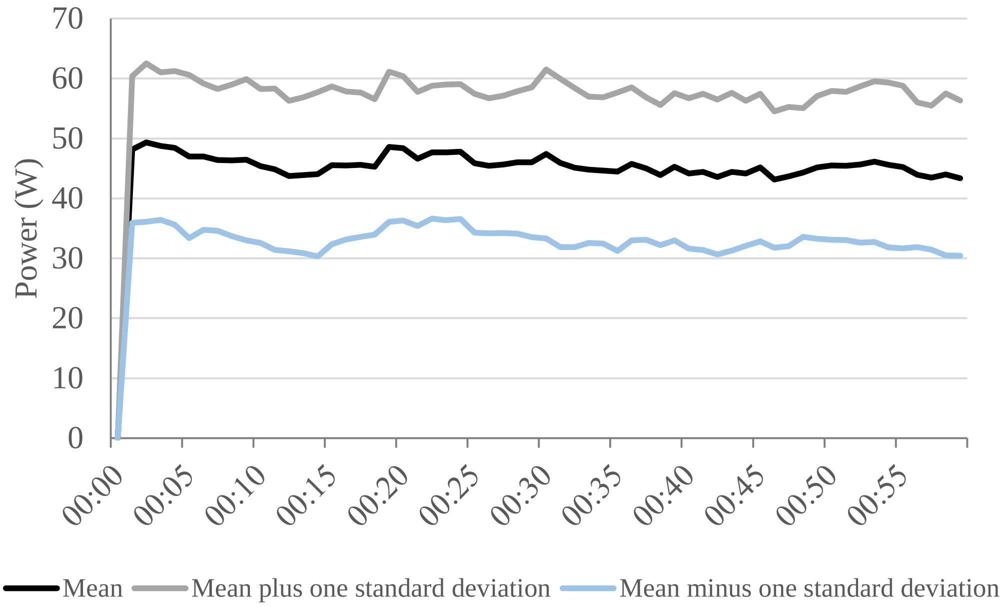


Figure 22. Graph showing the cold appliance profile and associated standard deviation margins between 00:00 and 00:59 demonstrating edge effects observed in the cold appliance profile

After this point in the algorithm, expected values were observed throughout the day up until the end of the day where the final edge effect was observed. The effect observed here was a consistent increase in the cold cycling profile at constant gradient from around 23:30 up until the end of the day (Figure 23). This effect was caused due to the running averages which are necessary to decide whether the cold cycle should be ON. Since the typical cold cycle in this project is ON for up to around 30 minutes per cycle, then when the algorithm begins to compare data against data which is beyond the cells in the dataset then the cold cycle will appear to the algorithm as always being ON. As more and more cycles appear to be turned ON, a gradual rise in the profile was observed which manifests itself as the edge effect observed in Figure 23.

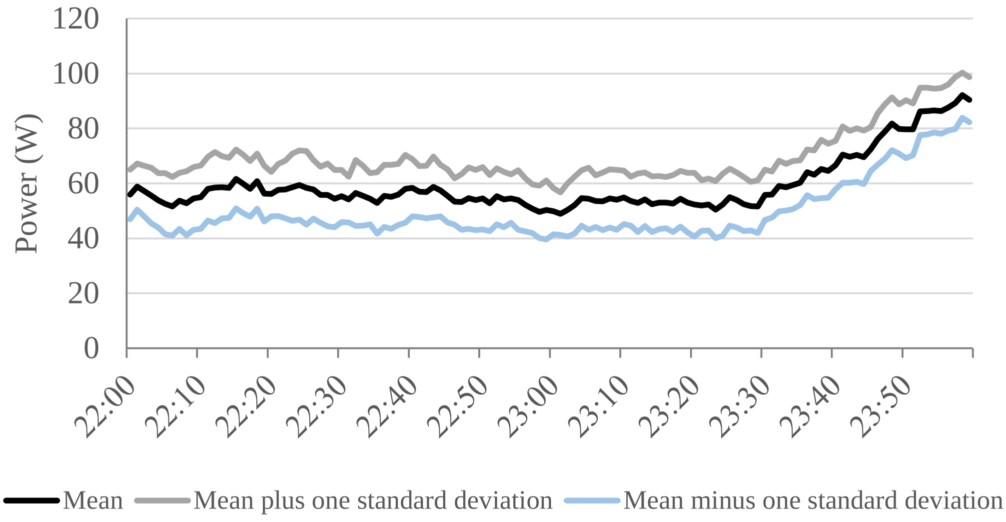


Figure 23. Graph showing the cold appliance profile and associated standard deviation margins between 22:00 and 23:59 demonstrating edge effects observed in the cold appliance profile

Whilst these edge effects were not desirable, they were fairly insignificant in size and fall away from the peak times which were of particular interest to this project. Furthermore, since the sum of all of the profiles were constrained to be equivalent to the total observed profile, each of these effects were absorbed by the auxiliary profile at the beginning and end of the day.

4.3. Analysis of Appliance Types

4.3.1. Total Profile

The average electricity usage for a property in this sample was found to be 10.8 kWh per day which is greater than the typical UK electricity consumption of 9.0 kWh per day (3,300 kWh per year) (Ofgem, 2011) and below the high consumption value of 14.0 kWh per day (5,100 kWh per year) (Ofgem, 2011). The higher than average figure could partly be explained by the time of year that this sample is based on. Higher than average figures would be expected since winter consumption is being compared to yearly averages. However, it also possible that this higher than average result is due to the sample being unrepresentative of the UK population.

The standard deviation of total daily electricity usage between days was 0.6 kWh. This represents 5.5% of the total mean.

The total load profile for a typical dwelling on a weekday in this sample is shown in Figure 24. This profile shows that peak occurs at 19:17 on a weekday and generally peak times are between 18:27 and 19:57.

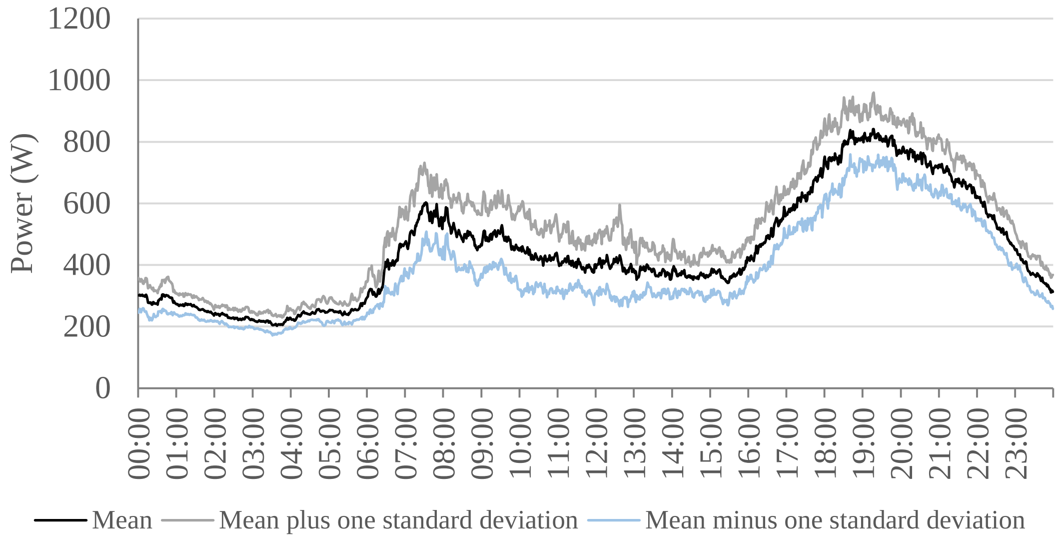


Figure 24. Typical total profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

4.3.2. Base Load

In order to estimate the 'typical' base load of a property in the sample of properties which were used in this project, the base load at each minute interval was averaged across each of the properties, this was repeated for each day in the dataset. With this averaged data, the typical base load was calculated by averaging across the different days in order to generate a profile which represents the average of 51 properties across 28 days. The mean base load power usage was found to be 81 W. The standard deviation of the base load was calculated based on the variation across the different days rather than the variation across the properties, as this provides more interesting insights since that is the variation which a network operator would be likely to see (they may not be as interested in the variation across different properties). The base load standard deviation was found to be 6 W. This small standard deviation of 7.5% compared to the mean is expected, as only a small variation would be expected from day to day. Since the base load is a measure of the underlying electricity consumption across the day, the profile for the base load is constant throughout the day as shown by Figure 25.

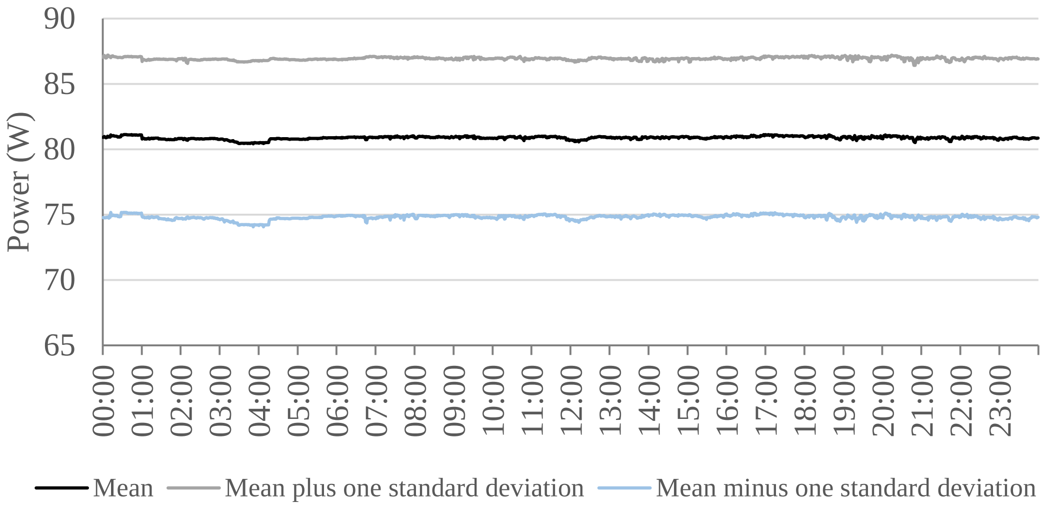


Figure 25. Typical base load profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

The variation in the base load for each day during the month is shown by Figure 26 below. This variation is caused by a number of factors. The first is the natural variation in the base load from residents adding to or taking away from their base load over time. Examples of actions which may affect the base load include; purchasing new electronics which draw standby power and taking action to reduce their consumption by switching off a television at the socket when going on holiday. The other main cause of the variation in the base load over the month is associated with problems with the algorithm which are reported in the previous section. Namely that the algorithm struggles to identify the correct base load when there is missing data for a particular day.

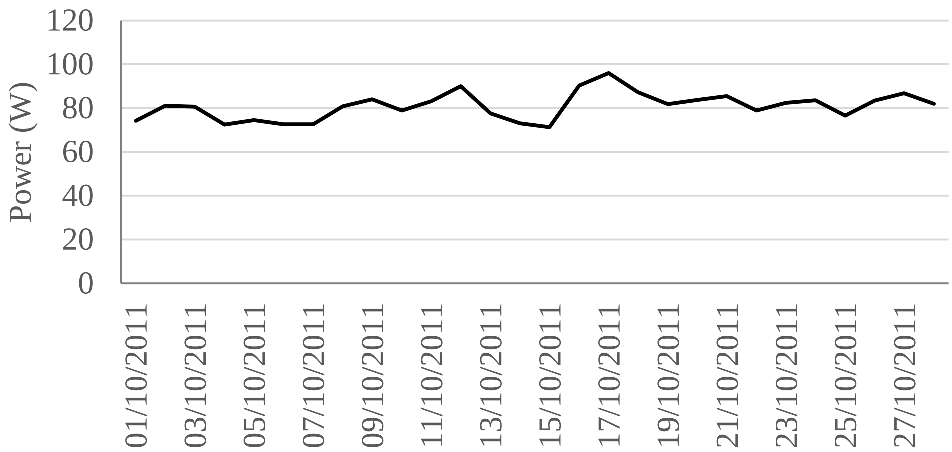


Figure 26. Average daily base load value for all properties in the sample from the 1st – 28th October 2011.

4.3.3. Heating Elements

The electricity usage associated with heating element appliances (excluding electric showers) was found to make up a substantial portion of the total electricity usage. As can be seen from the profile in Figure 27, there is very little electricity usage associated with heating elements overnight, particularly between 01:00 and 06:00. Between 06:00 and 08:00 electricity usage ramps up significantly to the morning peak at around 08:00. Usage remains relatively stable throughout the day, decreasing gradually until 16:00, with a small increase over the lunch period (11:30 – 13:00). From 16:00 to 19:00, usage rises steadily until it reaches the daily peak at around 19:00. From 19:00 onwards usage decreases steadily until the end of the day.

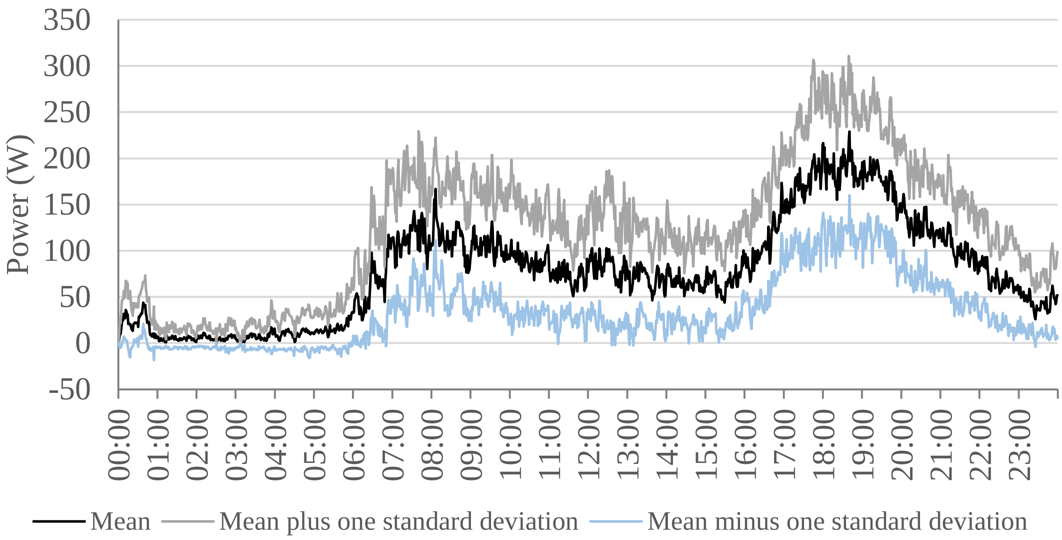


Figure 27. Typical profile of heating element appliances (minus electric showers) for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

4.3.4. Electric Showers

The sample of properties used in this project had a low penetration of electric showers at 14% (7 out of 51 properties, including 1 property which only recorded 2 events throughout the 28 days). This is lower than the expected ownership rate of electric showers in the UK, which is believed to be much higher, with estimates at 35% (Paula Owen Consulting, 2006) or 40-50% (Walker, 2009). Due to the low penetration of electric showers in the sample, the overall impact that electric showers could have, if they were to be targeted with a peak energy reduction intervention is low and for this study possibly also underestimated. This issue will be addressed in more detail in further sections but for now the observed electricity consumption of electric showers is considered.

Based on the sample used in this project electric showers use 0.1 kWh per day on average, approximately 1% of the total electricity usage, with the power usage associated with electric showers reaching a peak at 07:30 in the morning, as shown in Figure 28.

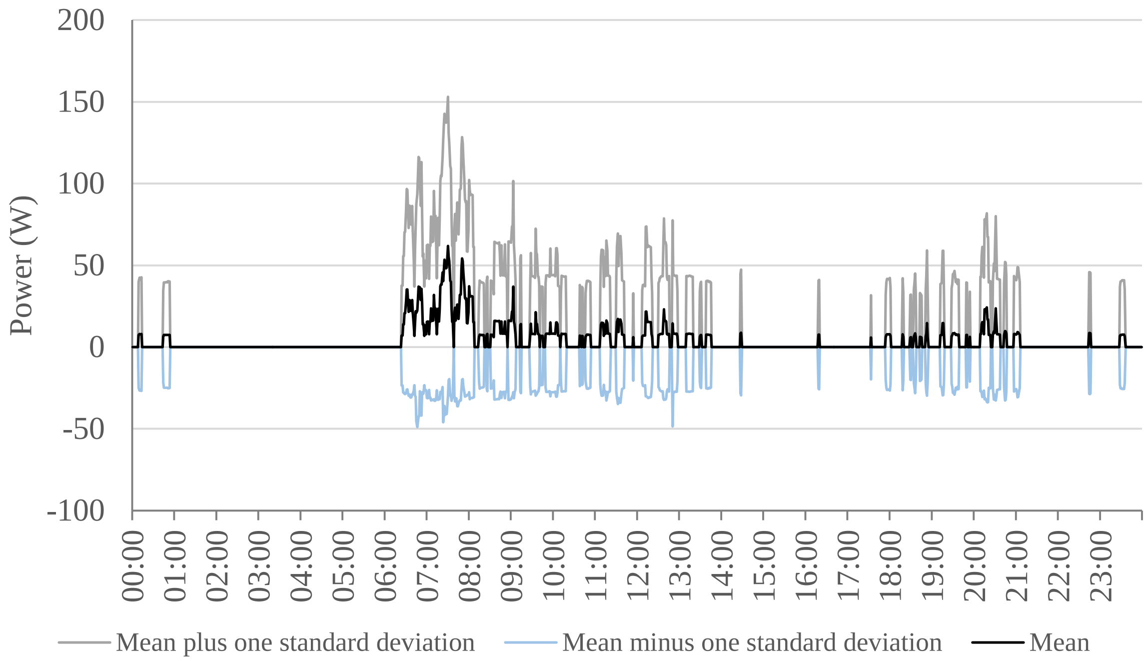


Figure 28. Typical electric shower profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

Considering only the properties where electric shower events were observed led to substantially different observations. This smaller sample of 7 properties had a much higher total daily electricity usage of 14.7 kWh (compared to 10.8 kWh for the entire sample). Some of this additional energy was used by electric showers which averaged 0.7 kWh in this subset of the sample (compared to 0.1 kWh) bringing the percentage of electricity used for electric showers up to 4.7% of the total. Interestingly, in these properties electricity usage was up across all the appliance type categories not just in the electric shower category.

4.3.5. Cold Appliances

Cold appliance profiles for each dwelling were determined algorithmically based on 3 input parameters. The required parameters were the duration of the ON and OFF segments of the cycle and the power usage when the appliance was ON. These were determined manually for each dwelling by identifying a period of stable electricity consumption at each dwelling, usually overnight. Lists of the time periods and parameters for each dwelling are provided in Appendices C and D.

Using the parameters observed during these periods it was possible to calculate a theoretical continuous power for each dwelling. The average continuous power usage calculated using this method for all of the dwellings was 55 W. This is higher than the stated average continuous power of more modern fridge-freezers which are in the range of 25 $W_{continuous}$ – 45 $W_{continuous}$ (Appendix E) (DSG Retail, 2014e; DSG Retail, 2014f; DSG Retail, 2014g; DSG Retail, 2014h).

Once the parameters were added to the algorithm, it was able to generate a profile based on when the cold cycles were believed to be ON. This method estimated that the average continuous power usage was 52 W, with a daily electricity usage attributed to cold appliances of 1.2 kWh. The profile for cold appliances is shown in Figure 29. As anticipated, it is mostly stable throughout the day. However, there is a trend throughout the day which resembles a less pronounced version of the total daily profile. This trend is believed to be related to the algorithm inadvertently being affected by the total trends through the running averages. An example of this is observed in Figure 29, where a slight peak is observed between 07:00 and 09:00, consistent with the morning peak in total demand.

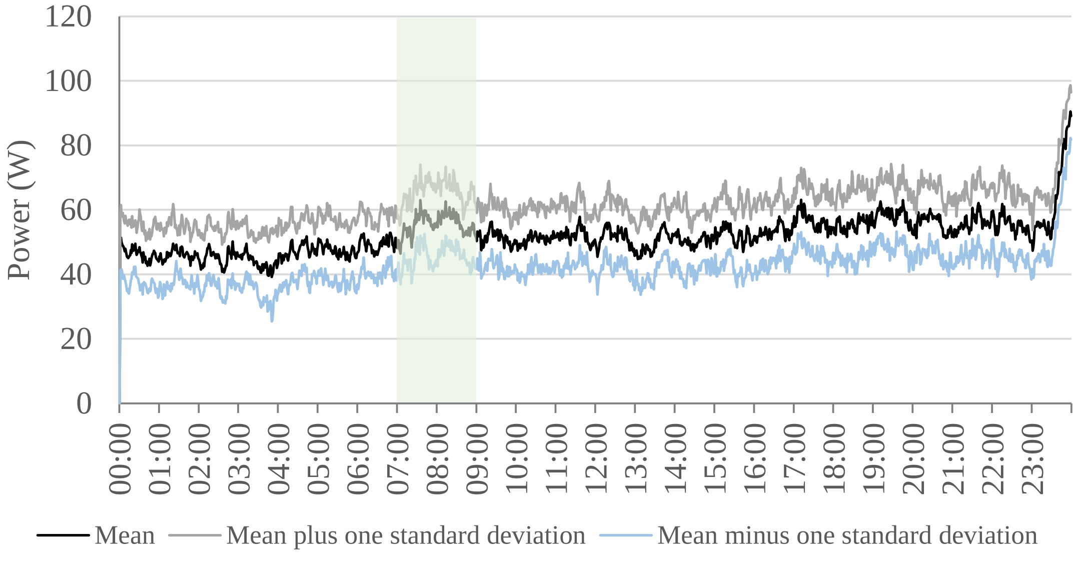


Figure 29. Typical cold appliance profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

For the purposes of peak load analysis (see 4.5.3), a number of options were considered which would serve to most accurately represent the cold cycle during the peak times. Since the algorithm is not believed to work particularly effectively during times of unstable electricity consumption, a surrogate dataset was considered to replace the cold cycle data during this point for peak analysis. The data which was considered was data from 03:00 to 04:30 since this was likely to be a period of more stable electricity usage which as discussed previously generally provided more accurate results. However, when compared to the theoretical calculation of mean continuous power (Appendix D), data from the overnight period was believed to underestimate electricity usage by around 20%, whereas data for 18:27 to 19:57 (peak time) was found to be 1.9% above the theoretical value and hence the 18:27 to 19:57 data was retained.

4.3.6. Lighting

As discussed previously, this report will only focus on the estimated lighting load in the evenings between the median sun set times of October (18:15) and June (21:21).

By averaging the power consumption of the lighting profiles for the properties included in the sample, for each minute and day of the month and then subsequently averaging each of the days for each minute it was possible to determine a typical lighting load profile for the sample, as shown in by the profile in Figure 30 below. The standard deviations used in Figure 30 are the standard deviations for each minute comparing each of the days. The average power consumption calculated for lighting between 18:15 and 21:21 is 165 W, which corresponds to 516 Wh/day.

Figure 30. Typical lighting profile for a subset of 10 properties from the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 and 1st and 28th June 2011. Additionally showing the mean profile plus and minus one standard deviation

In order to estimate the potential of lighting to contribute peak load reduction, each property was modelled assuming that all traditional bulbs were replaced with low energy equivalents. The current proportion of low energy bulbs found in each property was determined from survey data and is summarised in Table 1 below. The proportion of low energy lighting found in this sample of properties was 32%.

*Table 1. Results of the housing survey which indicate the proportion of low energy lighting found in the properties used for the lighting analysis. *Data was not available for this property and the average of the sample was used*

House ID	Standard	Low-Energy	% Low Energy
1	-	-	32%*
8	8	21	72%
9	-	-	32%*
10	28	9	24%
14	32	8	20%
15	11	9	45%
16	27	3	10%
18	34	16	32%
19	31	3	9%
20	11	9	45%
			32%

The lighting profile was then modelled a second time, however in this instance the standard bulb proportion of each property was assumed to have been replaced with low energy bulbs which required 80% less energy than the current standard bulbs (Energy Saving Trust, 2014b). This resulted in the profile shown in Figure 31. Comparison of the average lighting profile observed across the 10 properties as they were observed and as modelled under the low energy lighting intervention.

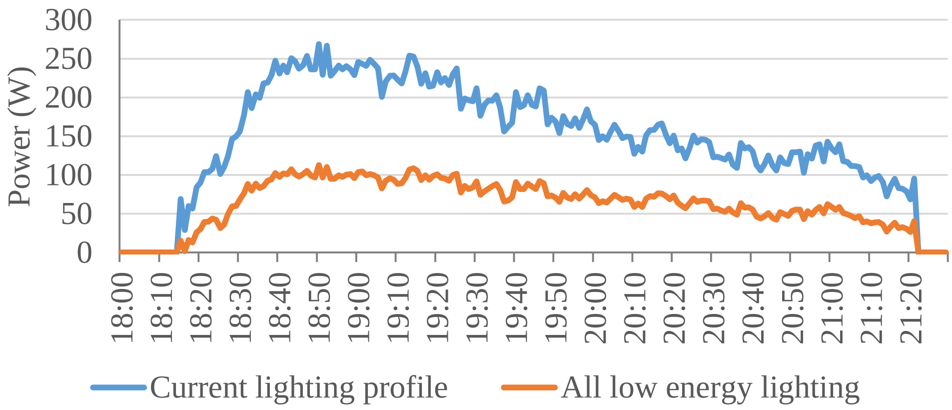


Figure 31. Comparison of the average lighting profile observed across the 10 properties as they were observed and as modelled under the low energy lighting intervention

4.3.7. Uncharacterised Appliances

All remaining electricity usage was grouped together in a profile which represents uncharacterised appliances which are believed to be appliances types including audio-visual, wet appliances, personal electronics, computing and storage heaters.

Under the current algorithm, the uncharacterised portion makes up 47% of total electricity usage on a daily basis (5.1 kWh/day of 10.8 kWh/day) and follows the profile shown in Figure 32.

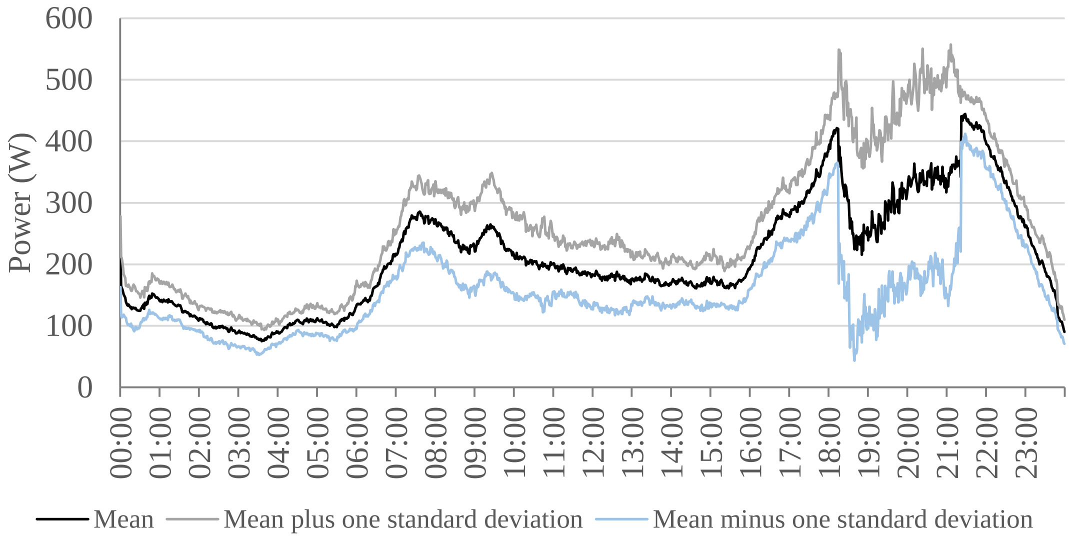


Figure 32. Typical uncharacterised profile (with lighting removed) for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

Due to the relative uncertainty associated with the lighting element of this algorithm, the uncharacterised profile prior to lighting analysis is also included for reference (Figure 33). The comparison of Figure 32 and Figure 33 also shows the large variation that is created on a daily basis from the lighting analysis. Observed in the increased standard deviation of the uncharacterised profile after lighting is removed (Figure 32) between 18:15 and 21:21.

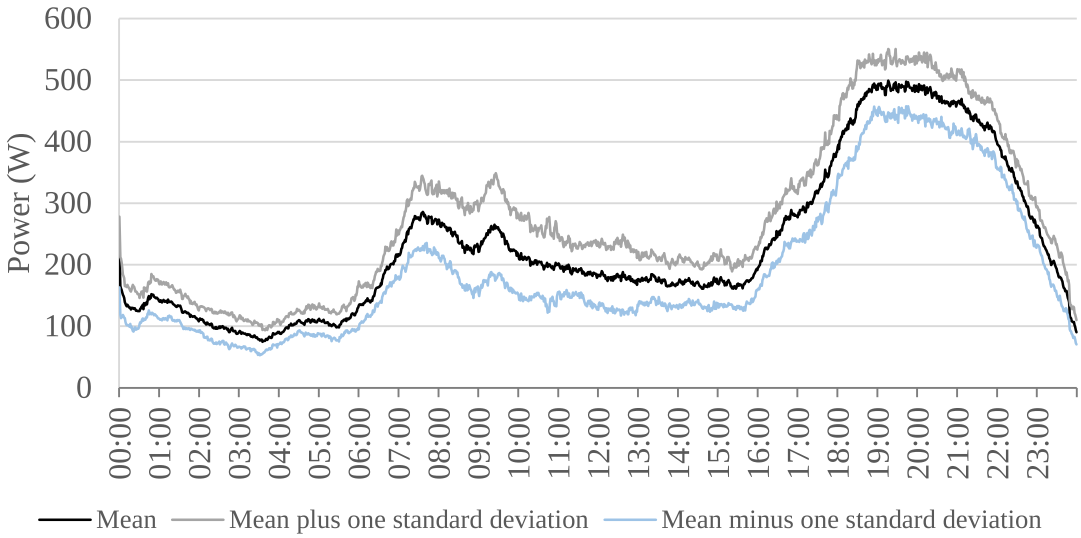


Figure 33. Typical uncharacterised plus lighting profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011. Additionally showing the mean profile plus and minus one standard deviation

4.4. Aggregated Mean Profile

Once each of the appliance type profiles had been successfully identified and individually analysed, the next stage was to consider how these appliances contribute towards the total domestic load. Table 2 summarises the daily electricity consumption that each of the appliance types is responsible for according to the algorithm used in this project. The standard deviation for each appliance type is a measure of the daily variation for that appliance type. For example in this case heating element consumption varies more from day to day than the base load does, despite a similar overall electricity consumption, as would be expected.

Table 2. Summary of the electricity consumption associated which each appliance type

	Daily electricity use (kWh/day)	**Standard deviation (kWh)**	**Percentage of daily use (%)**	**Time of maximum**
Total	10.8	0.5	100%	19:17
Base load	1.9	0.1	18%	16:57
Cold appliances	1.2	0.0	11%	23:58
Heating elements	1.9	0.2	18%	18:40
Electric showers	0.1	0.0	1%	07:30
Lighting	0.5	0.3	5%	18:50
Uncharacterised	5.1	0.4	47%	21:28

The total load profile broken down into component parts is shown below in Figure 34. This profile clearly shows that the base load and cold appliance electricity consumption remain relatively constant throughout the day with the remaining appliance types showing greater variability and peaking twice throughout the day, in the morning between 07:00 and 09:00 and in the evening between 18:30 and 20:00.

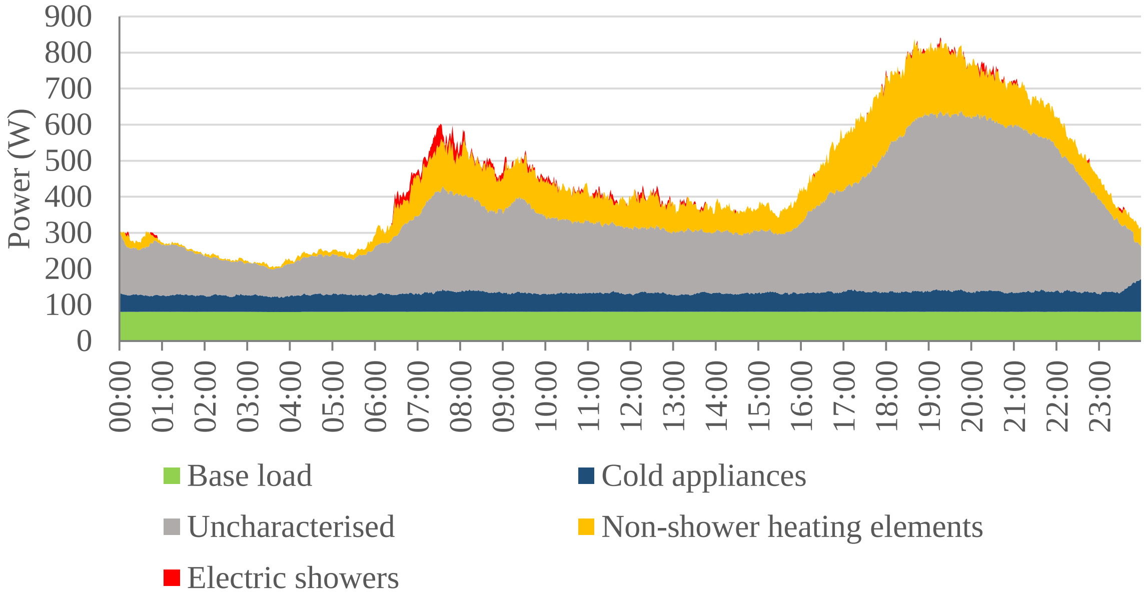


Figure 34. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 not including lighting

The profile shown above (Figure 34) does not distinguish the contribution of lighting to the overall profile, due to uncertainties associated with the sample size of the lighting analysis. However, the profile shown below in Figure 35 attempts to demonstrate as far as possible that contribution that lighting makes towards the total load profile.

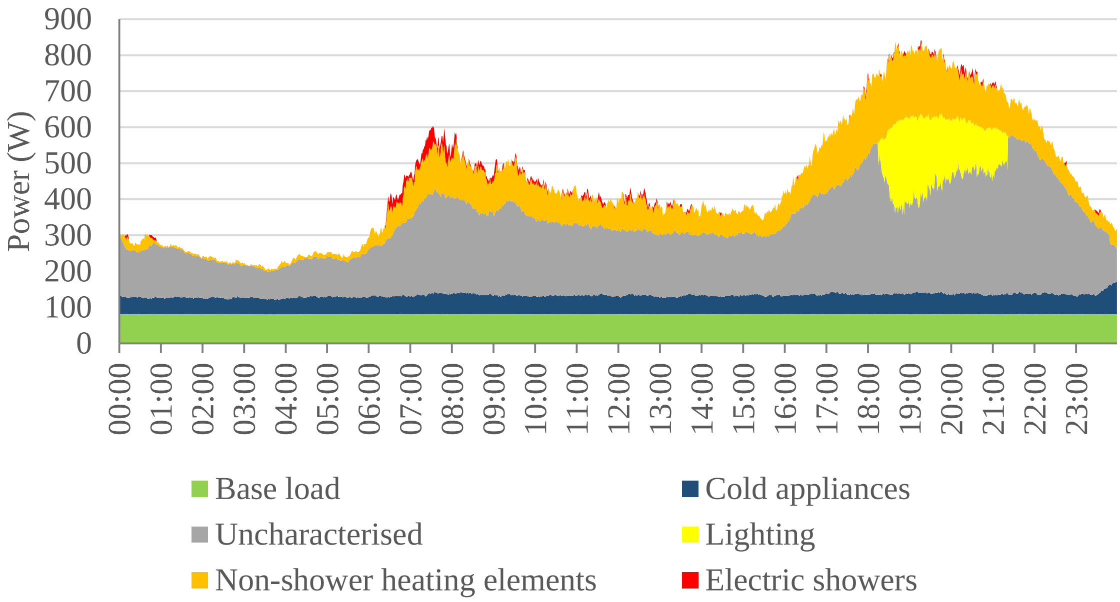


Figure 35. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 including lighting

4.5. Peak Load Reductions

4.5.1. Introduction to Peak Load Reductions

Whilst SSE have stated that their peak demand occurs between 20:00 and 21:00 on weekdays (James, 2014), this was not observed in this project. For this project the highest peak which was identified occurs between 18:27 and 19:57 on weekdays, as can be seen in Figure 35 above. Since this is the time identified by this analysis as the most threatening to local substations, this is the time that will be focused on for the peak load reduction interventions discussed here.

4.5.2. Low Energy Lighting

Replacing standard light bulbs with low energy light bulbs, offers an effective means of reducing domestic electricity demand both in general and at peak times. As mentioned previously this intervention was modelled by assuming that all currently used standard light bulbs would be replaced with energy efficient versions which use 80% less energy. The result is a consistent decrease in energy use at all times when lighting is in operation, as shown by the profile in Figure 36. This profile shows that the theoretical impact of this intervention in this sample of houses would have been significant. Overall this measure could account for a load reduction of 122 $W_{continuous}$ over the peak period which accounts for a reduction of 15.1% of total peak consumption.

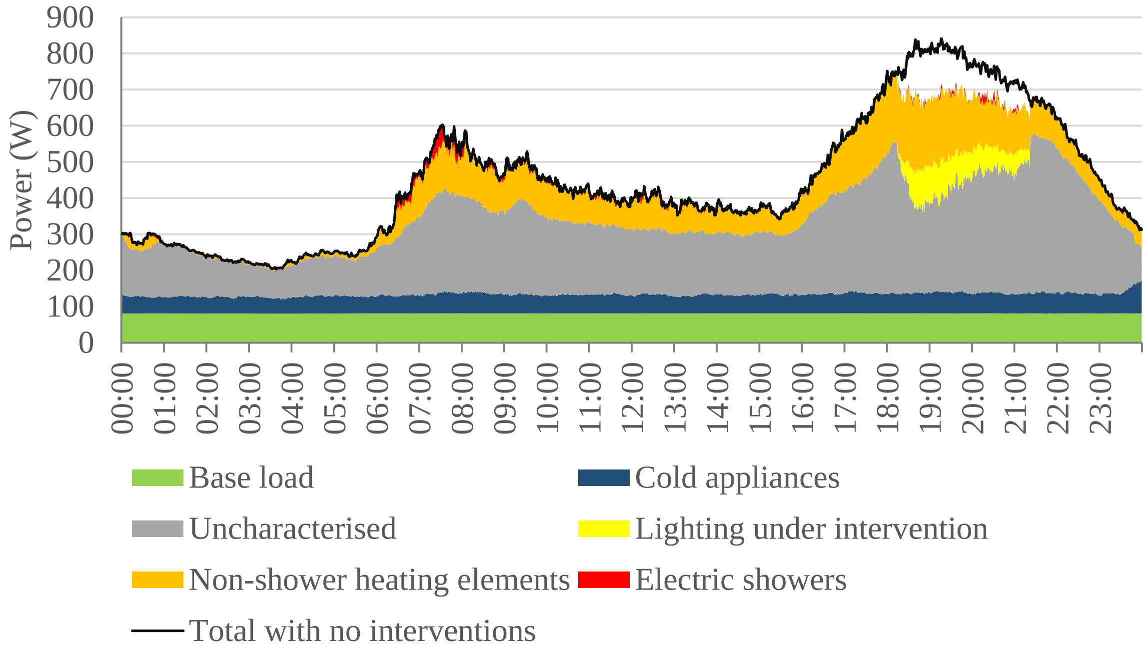


Figure 36. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the low energy lighting intervention

For a typical weekday low energy lighting serves to decrease electricity consumption associated with lighting by 58% (from 0.516 kWh per day to 0.219 kWh per day).

4.5.3. Cold Appliance Shifting

Another intervention which was considered in this project, is to remotely switch off fridges and freezers during the peak period, since in most cases this action can be performed for short periods of time with little change in the internal environment of the appliance and minimal spoiling of food.

For this project this was modelled by setting the cold appliance profile to zero during the peak period. In theory this can achieve a reduction of 58 $W_{continuous}$ equivalent to 7.1% of total peak demand. The new load profile for these properties had this intervention been implemented is shown below in Figure 37.

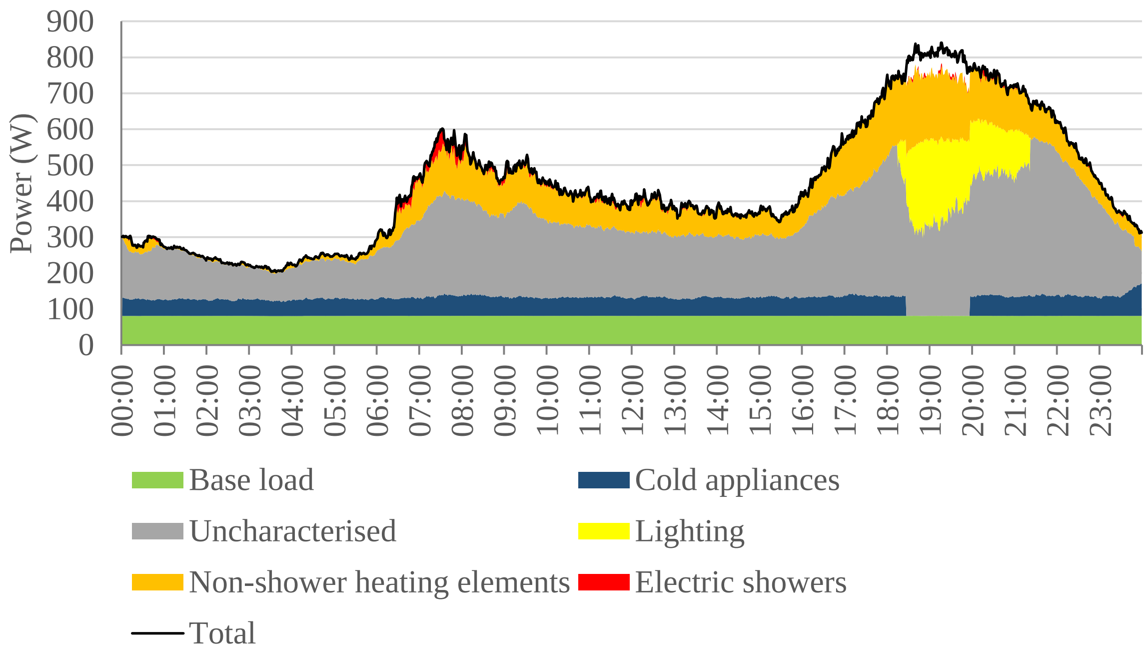


Figure 37. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the cold appliance intervention

The energy saved by switching off all compressors for the peak period would need to be supplied at some point, in order to return the appliance back to the correct internal temperature. It is uncertain what the profile of this consumption would resemble, however it has been simplistically modelled in this project by adding the energy avoided during peak to the profile at a later stage, this is shown by the profile in Figure 38.

This creates an issue, in that the shifted consumption creates a new peak in the shoulder period and hence does not solve the original problem of reducing peak demand. If implemented this intervention would need to be considered carefully and any surges in power post peak would need to be carefully managed.

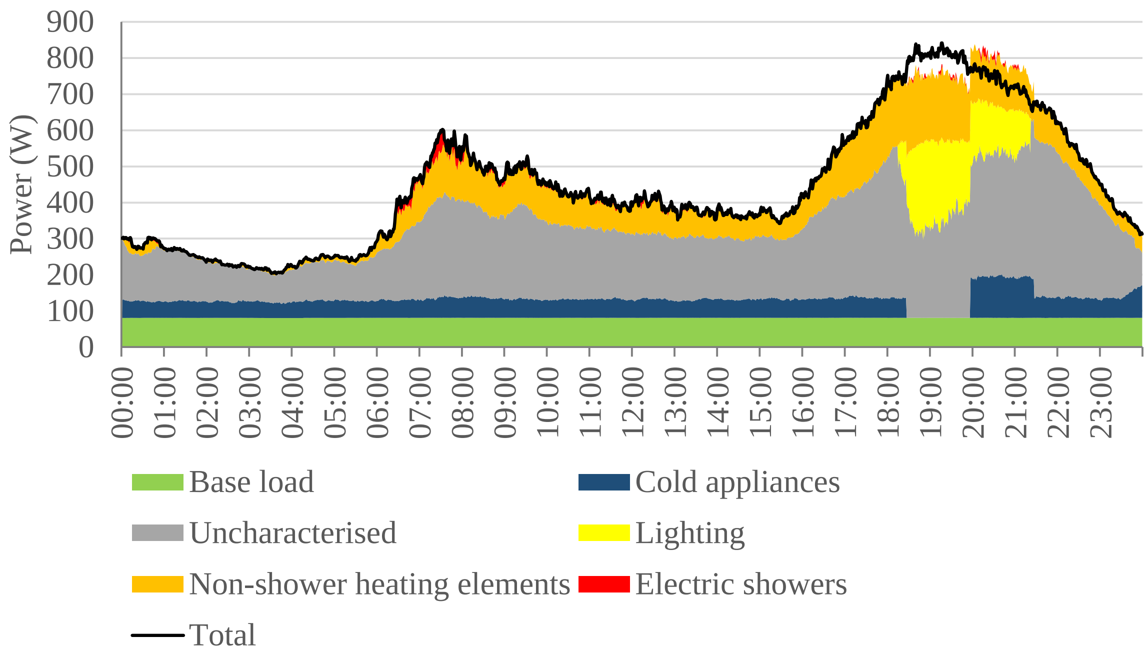


Figure 38. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the cold appliance intervention and highlighting the possible surge in power once appliances are switched back on

4.5.4. Electric Shower Shifting

The final intervention considered as part of this project involves encouraging residents to avoid using electric showers during the peak period. Despite their relatively infrequent use, electric showers pose an opportunity for load shifting due to their very high power consumption of 7 kW and over (Walker, 2009).

This project found a low penetration of electric showers (14% compared to ownership rates circa 40%), this had a significant effect on the impact that interventions targeting electric showers could have. With the observed figures assuming a 100% shifting of electric showers, they could contribute a reduction of 3 $W_{continuous}$ to the peak load or 0.4% of the total overall peak. This small impact is demonstrated by the load profile in Figure 39, where the reduction from electric showers can barely be seen.

It is feasible that in areas where there is a higher penetration of electric showers, reductions from these interventions may have a greater impact. Example of areas where this may be possible include, high density flats in urban areas (where showers are more popular in order to save space) and remote rural areas away from the gas network. Assuming the penetration of electric showers in similar locations is closer to the UK average ownership rate of 40% (roughly three times the sample penetration), it may be possible for electric showers to presents an opportunity of reducing peak demand by up to 1.2%.

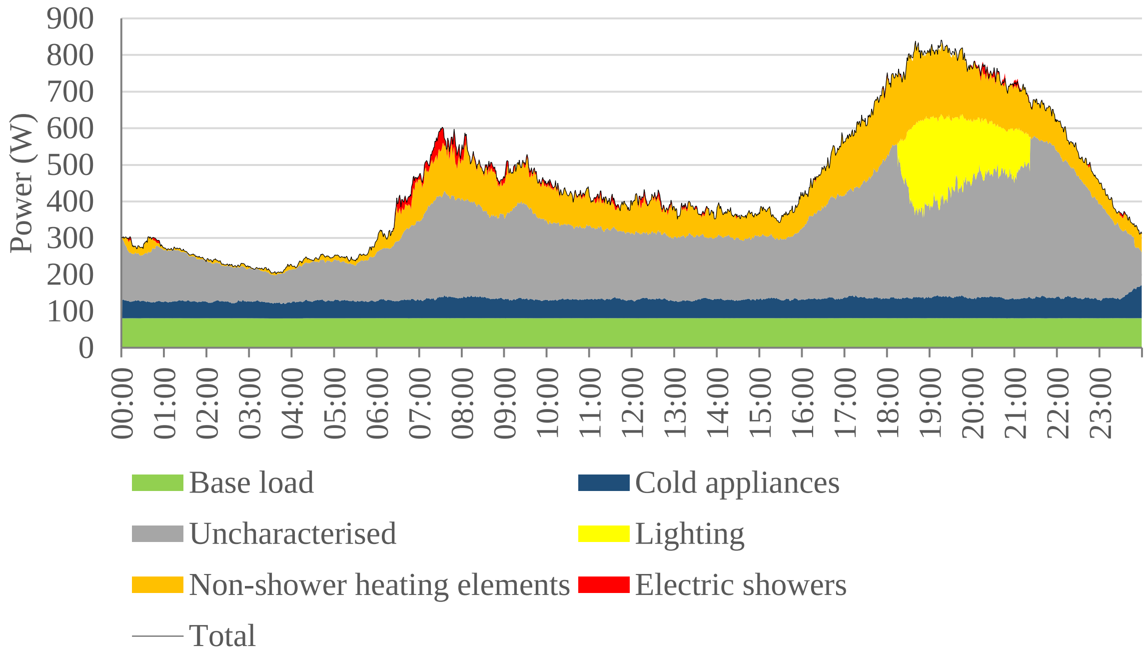


Figure 39. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of the electric shower intervention

4.5.5. Combined Impact

In order to determine what the impact of these interventions would be if they were implemented simultaneously, the above interventions are modelled together. The result is the profile shown below in Figure 40.

The total reduction is equivalent to the sum of each of the separate interventions, since the impact of each intervention is independent of each of the other interventions. Based on this analysis this is determined to be 182 $W_{continuous}$ which corresponds to a reduction of 22.6% of the total.

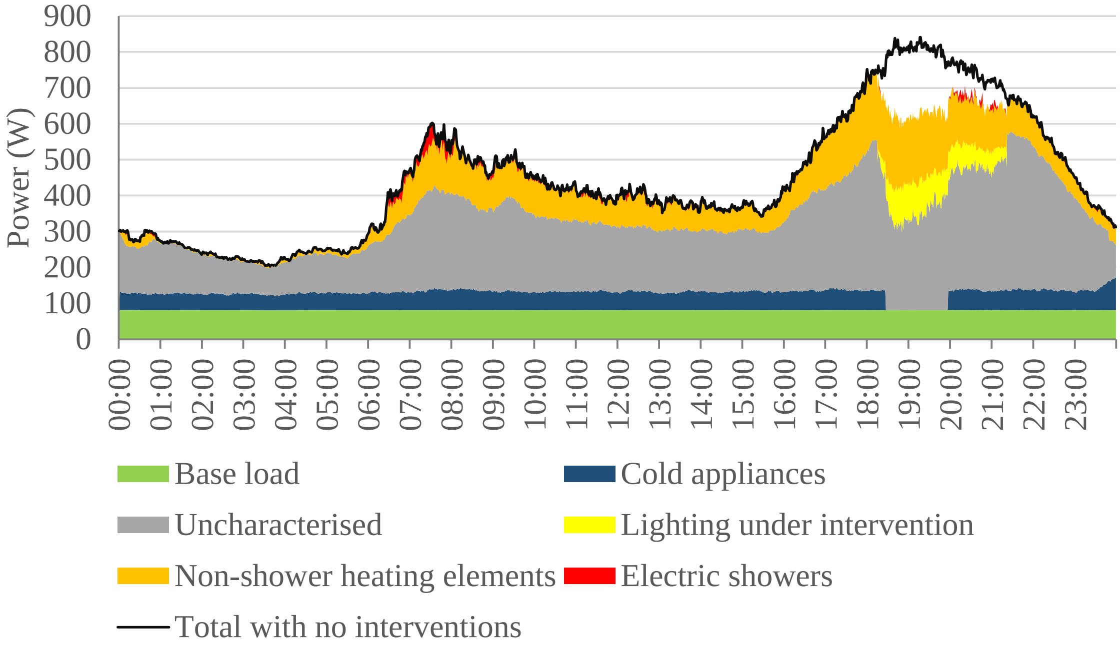


Figure 40. Average disaggregated profile for all properties in the sample generated using data from Mondays – Fridays between 1st and 28th October 2011 showing the impact of all interventions combined

Beyond the absolute peak which was identified to be between 18:27 and 19:57, there is also a reduction in electricity consumption in the shoulder period as shown in both Figure 40 and Figure 41.

Figure 41 shows the percentage of power that can be shifted for each minute. As mentioned above the percentage of power shifted from peak is an average of 22.6%. Figure 41 shows that it may also be possible to shift around 10% of consumption in the shoulder period, due to the low energy lighting intervention.

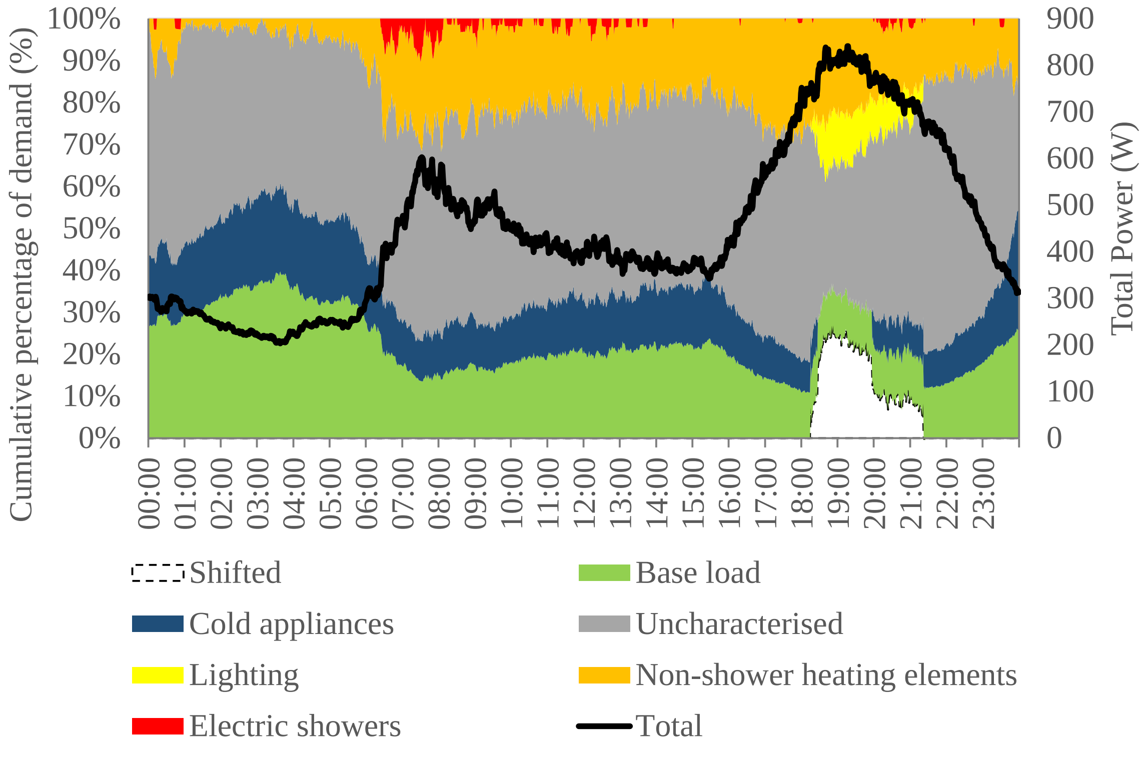


Figure 41. Average total demand profile plotted in black and showing the percentage of the total load which is made up by each appliance type for each time during the day. Highlighting the percentage reduction from which could be achieved at each point during peak

Whilst Figure 41 shows the power which can be avoided during the peak period, Figure 42 below shows which interventions the energy savings are coming from during the peak period.

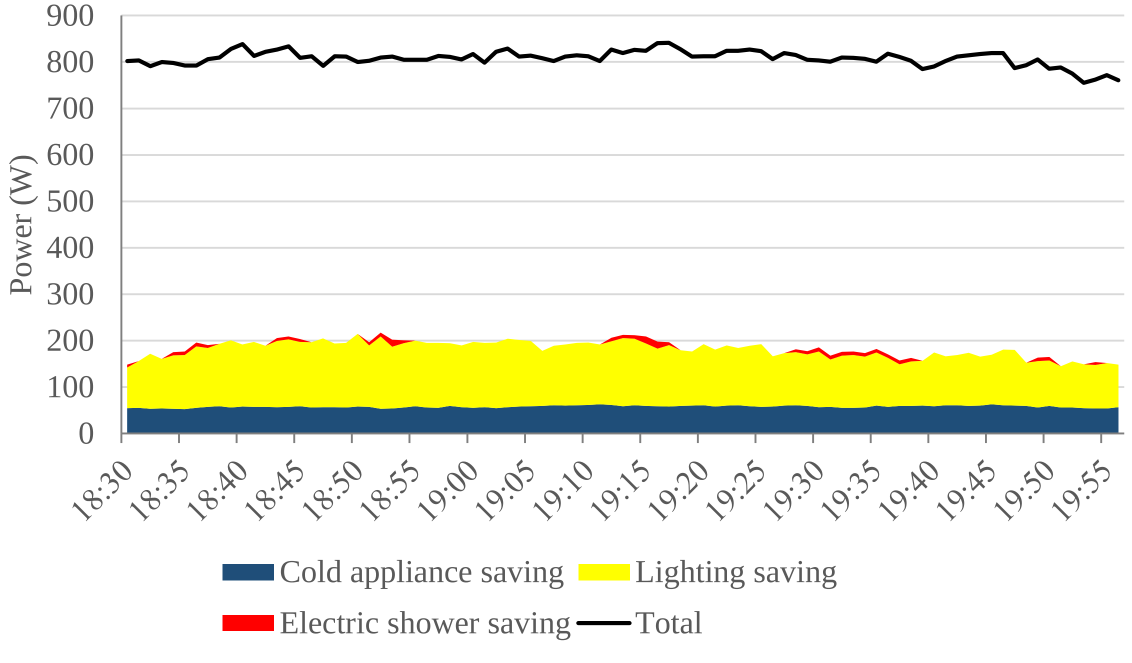


Figure 42. Average total power demand during peak times and showing the power consumption which could be avoided during peak times from each intervention

The headline results of analysis into the potential of the various interventions on peak load reduction are summarised in Table 3 below.

Table 3. Summary of the peak load reductions which could be achieved from each of the interventions

	Power Saving ($W_{continuous}$)	**Power Saving (% of total)**
Cold Appliances	58	7.1%
Low Energy Lighting	122	15.1%
Electric Showers	3	0.4%
Total Saving	**182**	**22.6%**

5. Discussion

5.1. Review of Appliance Types

5.1.1. Base Load

Based on a literature methodology, the base load for each household and day was calculated by identifying the minimum non-zero time interval during each day. This method was found to work well in most instances, however when the data was incomplete for a given day there were instances where the base load was underestimated, as explained in more detail in the results section of this report (see 4.2.1).

A potential strategy to improve this element of the algorithm, in particular to avoid the problems associated with incomplete data is suggested here. Adding an additional stage in the algorithm which excludes any cells adjacent to a null cell (i.e. a 1 minute interval directly prior to or following a 1 minute interval where data is missing and has a value of zero) may serve to address this issue. It is anticipated this could be included using conditional case based arguments (i.e. ***if*** previous cell does not equal zero ***and*** next cell does not equal zero ***then*** use value in base load algorithm ***if not*** exclude cell from base load algorithm). This method may add computational time to the algorithm, however the benefits would seem to outweigh the additional processing requirement. Another solution could be to add a manual overwrite option for each of the days and if the base load appears too low on a particular day then it could be manually updated with a more appropriate value. Whilst this would likely provide more accurate results, the added manual checking would seriously hinder the time required to conduct analysis.

As expected the base load profile was found to be very stable both throughout the day and from day to day, contributing a continuous 81 W to the typical property with a daily standard deviation of 6 W.

Due to the nature of the base load, no interventions were considered which may contribute to the reduction of the base load. Hence, this load is expected to stay the same following interventions in the SAVE project.

5.1.2. Heating Elements

The section of the algorithm dedicated to removing heating element spikes proved to be one of the most successful. In most instances the algorithm accurately identified and extracted heating element spikes in terms of both duration and magnitude.

A number of small problems were identified where the algorithm struggled to extract the entire profile in particular situations. These situations are where there is a 1 minute interval at the beginning or end of a peak where the peak value is below the peak threshold value or when the peak duration is greater than 11 minutes and the entire peak cannot be captured.

The first of these problems, related to values below the peak threshold value could be addressed in two ways. The first is to utilise a form of variable peak threshold, i.e. if it is known that for a particular house the cold cycling effect is always below 100 W, then it would be possible to decrease the peak threshold to a value between the current peak threshold of 500 W, whilst maintaining it above the cold appliance power usage. This method would be relatively straightforward to implement from the algorithm design perspective but would add more manual checks when running the algorithm to ensure the peak threshold value is appropriate. This strategy could also lead to the algorithm picking up an increasing number of features which would not normally be considered in the category of heating element spikes, presumably this trend would also increase as the peak threshold value decreased.

The next strategy proposed by the author would be to apply another layer to the heating element section of the algorithm. This layer would consider the profile which has just been created by the algorithm and look for instances where there are spikes (above a new lower threshold value) of precisely 1 minute, which would be a guaranteed characteristic of any peaks which were mistakenly not included on the edge of a real peak. The algorithm could then add these new smaller peaks to the heating element profile and generate a further smoothed total profile.

The second problem with the algorithm relates to peaks which have a duration over 11 minutes. Again there are two possible strategies to address this problem, the first being to re-assess whether the parameters of the algorithm are suitable i.e. should the sampling consider longer peaks and what should be the maximum duration of a peak. Initially the value of 11 minutes was decided as it was reasonable that most spikes would not exceed 11 minutes in duration, however it may be possible to increase this without causing the algorithm to start picking up too many other undesired features. Changing this parameter is a balancing act between including as many legitimate spikes as possible and avoiding the inclusion of non-spike features.

The alternative strategy to resolve this problem would involve designing a second layer for this stage in the algorithm. This layer would look at the new total profile and identify any peaks which identify pairs of peaks of very similar magnitude and duration which are 11 minutes apart (which is a feature directly related to this problem with the algorithm) and subsequently remove these pairs of peaks according to a similar algorithm to the current one.

The heating element profile which was generated as a result of this analysis follows the overall profile relatively closely, with very little usage overnight, a small peak in the morning, leading into stable usage during the afternoon followed by a large peak in the evening. Matching the profile which would be predicted considering the typical usage appliances in the home. On average heating element appliances are found to contribute 79 W to the total demand (17.5%).

5.1.3. Electric Showers

Electric shower events were identified based on the previously generated heating element profile. Any instances where the heating element spike was found to be greater than 6 kW were included in the electric shower profile and subtracted from the general heating element profile.

The success of the algorithm at accurately characterising electric shower events was verified by considering the distribution of 28 days' worth of electric shower events from one property. It was observed that distribution of both duration and magnitude of the events was reasonable for representing a properties showering routines.

Since electric showers are almost uniquely the most extreme events observed in a property (in terms of power magnitude) they proved to be straightforward to characterise. The only problem observed in the algorithm was that is occasionally identified an electric shower event in houses that likely did not have (or at least use) an electric shower. This was observed as occasional spikes of just over 6 kW (the electric shower threshold) which were probably the result of multiple appliances running simultaneously for a short period of time. In further versions of this algorithm this problem could be addressed by including an ON/OFF parameter for the electric shower section of the algorithm, allowing the user to selectively exclude properties from separating electric showers and heating element profiles.

One issue identified by this analysis was the low penetration of electric showers which were observed in the sample (14%), compared to literature data on national ownership rates of 35% - 50%. As a result the impact of electric showers on peak reduction was found to be small at around 0.4%. Whereas if the penetration of electric showers in particular area was closer to the national ownership rate, this would presumably rise up to higher levels between 1% and 1.4%.

The peak reduction potential of electric showers is also severely impacted by the time of day when electric showers are most commonly used. This analysis has found that most electric shower events occur in the morning between 06:15 and 08:15, whereas the total peak is in the evening between 18:27 and 19:57. In a situation where it was necessary or desirable to reduce the morning peak, electric showers may provide an opportunity to reduce peak demand.

This analysis has not considered a mechanism by which shifting of electric shower use would be achieved, just an upper bound for the possible reduction. Further research around how consumers would react to interventions to encourage them to avoid using electric showers during an evening peak would need to be conducted.

5.1.4. Cold Appliances

Cold appliances proved to be the most challenging appliance type to characterise during this project. Whilst it was possible to characterise the profile during times of stable electricity usage, the algorithm was much less successful at accurately identifying the cold appliance profile at peak times when the overall electricity usage profile was much more variable.

The method used in this stage of the algorithm, was for the user to manually identify a range of parameters associated with a cold profile and feed these into the algorithm to search for. However this method was found to be highly sensitive to the length of the cycling and levels of additional activity. Much more research would be required in this area to identify a suitable method of extracting the cold appliance profile. The key problem being that the magnitude of the power usage from cold appliances is relatively low compared to other appliances.

One problem with this element of the algorithm for which a potential solution has been considered is the edge effects. These are caused by the algorithm running against empty cells at the beginning and end of each day. The simplest solution to this problem would be to replace the intervals where edge effects are observed with the results observed at a time when the results are expected to be more accurate.

Despite the algorithm not being able to accurately identify the cold appliance profiles during the peak period, by comparing the algorithmically determined average usage to the theoretical cold appliance usage (calculated solely based on the parameters for each property), it was deemed that the algorithmically determined data was still representative from a typical property perspective. Hence it was possible to calculate a constant power usage of 58 W at peak.

For the purposes of this investigation, it was assumed that cold appliances could be switched off for the duration of the peak period, resulting in a peak reduction of 7.1% of the total. However, this investigation has not considered the mechanism which would be used to implement an intervention such as that. One of the largest questions which remain related to the cold appliance interventions is, what happens once the peak period is over and the cold appliances can be turned on again. Presumably a system would be developed to stagger the appliances which are turned back on, in order to avoid a surge in power, leading to a new peak. The second major question which would require further research relates to how long a cold appliances can be forced to switch off for, without risking the quality of the appliances service (spoiling the food in a fridge or freezer).

5.1.5. Lighting

The disaggregation of the lighting load was included in this project as a proof of concept. The method used to determine the lighting load over the peak period, was based on the assumption that the difference between the auxiliary profile (after each of the previously discussed profiles was removed) at two different times of year with different sun set times would give an indication of the lighting load for the time of year with the earlier sun set time. In this case the comparison was between October (median sunset time 18:15) and June (median sun set time 21:21). However, it is acknowledged by the author that this analysis attributes all variation between the seasons to lighting appliances, whereas other appliance types may also be contributing to the difference between the two seasons. For example tumble dryer and electric heater usage increasing between the seasons. Hence, the lighting load and subsequently the lighting load reductions may be overestimated by this analysis. Therefore, this analysis only serves to provide an upper estimate of the lighting reductions which could be achieved.

This method provided intuitively reasonable results, with an estimate of 165 W of continuous power being used by lighting in a typical property. Once a baseline electricity consumption from lighting was established, the possibility of peak reduction from lighting was modelled. The first step was to identify the proportion of lighting from of each property which was currently being supplied by low energy lighting from survey data collected at each property. The next stage was to model the reduction in peak demand by assuming that all non-low energy lighting would be replaced with low energy lighting requiring 80% less energy. The result was a new profile using entirely low energy lighting.

The findings from this analysis suggest that it would be possible to reduce peak energy consumption by 15.1% (122 W).

In order to streamline an algorithm which disaggregated the load profile of lighting, it would be necessary to incorporate this element of the analysis into the current tool, as the manual processing required at present is a significant barrier to carrying this analysis out on larger samples than the current subset of 10 properties and hence obtaining more reliable results.

5.1.6. Uncharacterised

The uncharacterised profile represents the remainder of the energy usage once all of the identifiable appliance types have been extracted. This contains a range all appliances which don’t have an easily identifiable load signature or unpredictable use, such as computing and audio-visual equipment, personal electronics, chargers and wet appliances, amongst others. For the current algorithm this uncharacterised portion makes up just under half of all energy consumption (47%), hence it would interesting if further research could serve to identify more appliance types from within this profile, in order to determine whether there is scope for further peak load reductions.

One such appliance type which should be identifiable in a load profile is storage heaters. These are characterised by long durations (greater than one hour) of high power consumption (2-3 kW) often overnight. The number of properties with storage heaters is expected to be low but the high electricity consumption by this appliance type could serve to identify at least a further component of the uncharacterised profile.

5.2. Alternative Data Resolutions

Analysis which considers alternative data resolutions is identified as an area of potential further work. The data resolution used in this project (1 minute) was used as it allowed for most of the appliance features of interest to remain identifiable whilst minimising the data which needed to be stored and processed.

Further projects may require the use of higher or lower resolution data. Datasets with smaller numbers of properties and shorter time periods may have higher resolution (~1 second) data available. In these instances it may be possible to use the higher resolution to more accurately identify appliance signatures and hence generate more accurate appliance type profiles and possibly to extract more appliance types from the uncharacterised profile. One interesting means of achieving this would be to look into the delta form of the profile, which considers not the total energy at a point in time but how it has changed from the previous interval. This method should allow the identification of each appliance being switched on or off.

On the other hand, it is unrealistic to assume that it would be possible to gather data at 1 minute resolutions for much larger samples of properties or over much longer timeframes. Such as when data begins to be gathered following the roll out of smart meters in the UK, for which meter readings are expected to be collected at 30 minute intervals. These problems encourage further research into what appliances and patterns can be extracted from total demand data at longer resolutions (5 - 30 minutes)

5.3. Conclusion

This project was successful in achieving each of its primary objectives. Firstly, an algorithm was created which is capable of deconstructing measured total electricity demand of dwellings into base load, heating element, electric shower, cold appliance, lighting and uncharacterised parts, with over 50% of energy consumption being characterised when applied to a sample of data from the energy and communities project. Once this stage of the project was successfully achieved, 3 peak demand reduction interventions were modelled, these were to supply low energy lighting, switch off cold appliances during peak and prohibit the use of electric showers during peak. This analysis led to the conclusion that 15%, 7% and 0.4% of total demand could be avoided during peak due to each of those interventions respectively. This provides an estimate to the SAVE project of what an upper limit of the interventions they are considering may produce in terms of peak load reductions.

5.4. Future Work

Two main avenues exist to build on the work carried during this dissertation. The first involves increasing the proportion of the total load which is characterised by the algorithm. Just under 50% of the total demand remains uncharacterised and it would be interesting to add new processes to the algorithm which are able to determine additional appliance types. The appliance types which are currently considered as opportunities are storage heaters and tumble dryers. Storage heaters have a distinctive load profile as described previously (see 5.1.6) and hence could relatively easily be identified from within the total profile, making them an attractive target for further characterisation. Tumble dryers and other shiftable loads such as dishwashers and washing machines are another area worthy of further research due to the impact that they could have on peak load reductions as identified in the literature review (see 2.3.6).

The second avenue for future work focuses on creating a disaggregation methodology suitable for use on datasets with lower resolution (15 – 30 minutes), such as that of the SAVE project and data gathered from the smart meter rollout.

6. References

AECOM, 2011. *Energy Demand Research Project: Final Analysis Executive Summary,* St Albans: AECOM.

Akbari, H., 1995. Validation of an algorithm to disaggregate whole-building hourly electrical load into end uses. *Energy,* 20(12), pp. 1291-1301.

Anda, M. & Temmen, J., 2014. Smart metering for residential energy efficiency: The use of community based social marketing for behavioural change and smart grid introduction. *Renewable Energy,* Volume 67, pp. 119-127.

Bardsley, N. et al., 2013. Initial Effects of a Community-Based Initiative for Energy Saving: An Experimental Analysis.

Birt, B. J. et al., 2012. Disaggregating categories of electrical energy end-use from whole-house hourly data. *Energy and Buildings,* Volume 50, pp. 93-102.

Buchanan, K., Russo, R. & Anderson, B., 2014. Feeding back about eco-feedback: How do consumers use and respond to energy monitors?. *Energy Policy,* Volume 73, pp. 138 - 146.

Chahine, K. et al., 2011. Electric Load Disaggregation in Smart Metering Using a Novel Feature Extraction Method and Supervised Classification. *Energy Procedia,* Volume 6, pp. 627-632.

Commission for Energy Regulation, 2011. *Electricty Smart Metering Customer Behaviour Trials (CBT) Findings Report,* Dublin: Commission for Energy Regulation.

DECC, 2011. *Smart Metering Implementation Programme - Overview Document,* London: DECC.

DECC, 2013a. *Smart Metering Implementation Programme - Smart Metering Summary Plan,* London: DECC.

DECC, 2013b. *Smart meters: a guide.* [Online]
Available at: https://www.gov.uk/smart-meters-how-they-work
[Accessed 01 July 2014].

Dominguez-Navarro, J. A., Bernal-Agustin, J. L. & Dufo-Lopez, R., 2009. Data mining methodology for disaggregation of load demand. *Electric Power Systems Research,* Volume 79, pp. 1393-1399.

DSG Retail, 2014a. *BOSCH WTE84301GB Condenser Tumble Dryer - White.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/laundry-dishwashers/tumble-dryers/bosch-wte84301gb-condenser-tumble-dryer-white-21499907-pdt.html#longDesc
[Accessed 06 September 2014].

DSG Retail, 2014b. *ZANUSSI ZDEB47209W Vented Tumble Dryer - White.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/laundry-dishwashers/tumble-dryers/zanussi-zdeb47209w-vented-tumble-dryer-white-10023456-pdt.html
[Accessed 06 September 2014].

DSG Retail, 2014c. *HOOVER VTC671B Condenser Tumble Dryer - Black.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/laundry-dishwashers/tumble-dryers/hoover-vtc671b-condenser-tumble-dryer-black-10025815-pdt.html
[Accessed 06 September 2014].

DSG Retail, 2014d. *MIELE T8722 Tumble Dryer - White.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/laundry-dishwashers/tumble-dryers/miele-t8722-tumble-dryer-white-21487060-pdt.html
[Accessed 06 September 2014].

DSG Retail, 2014e. *BEKO CXFD5104W Fridge Freezer – White.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/refrigeration/fridge-freezers/beko-cxfd5104w-fridge-freezer-white-12635532-pdt.html
[Accessed 08 September 2014].

DSG Retail, 2014f. *SAMSUNG RL58GPEIH Fridge Freezer - Inox Stainless.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/refrigeration/fridge-freezers/samsung-rl58gpeih-fridge-freezer-inox-stainless-11318158-pdt.html
[Accessed 08 September 2014].

DSG Retail, 2014g. *LOGIK LFC50S12 Fridge Freezer – Silver.* [Online] Available at: http://www.currys.co.uk/gbuk/household-appliances/refrigeration/fridge-freezers/logik-lfc50s12-fridge-freezer-silver-12265403-pdt.html
[Accessed 08 September 2014].

DSG Retail, 2014h. *HOTPOINT FFU4DX Fridge Freezer - Stainless Steel.* [Online]
Available at: http://www.currys.co.uk/gbuk/household-appliances/refrigeration/fridge-freezers/hotpoint-ffu4dx-fridge-freezer-stainless-steel-17152055-pdt.html
[Accessed 08 September 2014].

Ehrhardt-Martinez, K., Donnelly, K. A. & Laitner, J. A., 2010. *Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities,* Washington D.C.: American Council for an Energy-Efficient Economy.

Elexon, 2014. *System Prices.* [Online]
Available at: https://www.elexonportal.co.uk/category/view/175?cachebust=142ea8mysf
[Accessed 22 August 2014].

Energy and Climate Change Committee, 2013. *Smart Meter Roll-Out: Government and Ofgem Responses to the Comittee's Fourth Report of Session 2013-14,* London: The Stationary Office Ltd.

Energy Saving Trust, 2014a. *Our calculations.* [Online]
Available at: http://www.energysavingtrust.org.uk/Energy-Saving-Trust/Our-calculations
[Accessed 24 August 2014].

Energy Saving Trust, 2014b. *Lighting products.* [Online]
Available at: http://www.energysavingtrust.org.uk/Electricity/Lighting/Lighting-products
[Accessed 21 August 2014].

ESRC, 2014a. *The role of community-based initiatives in energy saving.* [Online]
Available at: http://www.esrc.ac.uk/my-esrc/grants/RES-628-25-0059/read
[Accessed 05 September 2014].

ESRC, 2014b. *Census 2022: Transforming Small Area Socio-Economic Indicators through 'Big Data'.* [Online]
Available at: http://www.esrc.ac.uk/my-esrc/grants/ES.L00318X.1/read
[Accessed 31 July 2014].

European Commission, 2014. *Energy Efficiency Directive.* [Online]
Available at: http://ec.europa.eu/energy/efficiency/eed/eed_en.htm
[Accessed 22 August 2014].

Figueiredo, M., Almeida, A. D. & Ribeiro, B., 2012. Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems. *Neurocomputing*, Volume 96, pp. 66-73.

Gruber, J. K., Jahromizadeh, S., Prodanović, M. & Rakočević, V., 2014. Application-oriented modelling of domestic energy demand. *Electrical Power and Energy Systems*, Volume 61, pp. 656-664.

Hamidi, V., Li, F. & Robinson, F., 2009. Demand response in the UK's domestic sector. *Electrical Power Systems Research*, Volume 79, pp. 1722 - 1726.

James, P., 2014. *Project Meeting - Early August* [Interview] (August 2014).

Kerrigan, D. J., Gamberini, L., Spagnolli, A. & Jacucci, G., 2011. Smart meters: A users' view. *PsychNology*, 9(1), pp. 55-72.

Kilpatrick, R. A. R., Banfill, P. F. G. & Jenkins, D. P., 2011. Methodology for characterising domestic electrical demand by usage categories. *Applied Energy*, Volume 88, pp. 612-621.

Liang, J., Ng, S. K. K., Kendall, G. & Cheng, J. W. M., 2010. Load Signature Study-Part I: Basic Concept, Structure, and Methodology. *IEEE Transactions on Power Delivery*, 25(2), pp. 551-560.

Murtagh, N., Gatersleben, B. & Uzzell, D., 2014. 20:60:20 - Differences in Energy Behaviour and Conservation between and within Households with Electricity Monitors. *PLoS ONE*, 9(3), pp. 1-12.

National Grid, 2013. *2013 Electricity Ten Year Statement*, London: National Grid.

Ofgem, 2011. *Typical domestic energy consumption figures*, London: Ofgem.

Ofgem, 2013a. *Electricity Capacity Assessment Report 2013*, London: Ofgem.

Ofgem, 2013b. *Low Carbon Networks Fund submission from Southern Electric Power Distribution – Solent Achieving Value from Efficiency.* [Online]
Available at: https://www.ofgem.gov.uk/publications-and-updates/low-carbon-networks-fund-submission-southern-electric-power-distribution-%E2%80%93-solent-achieving-value-efficiency
[Accessed 22 August 2014].

Paula Owen Consulting, 2006. *The rise of the machines - A review of energy using products in the home from the 1970s to today*, London: Energy Saving Trust.

Perth Solar City, 2012. *Perth Solar City: Annual Report 2012*, Perth: Perth Solar City.

Richardson, I., Thomson, M., Infield, D. & Delahunty, A., 2009. Domestic lighting: A high-resolution energy demand model. *Energy and Buildings,* Volume 41, pp. 781 - 789.

Royal Academy of Engineering, 2013. *GB electricity capacity margin,* London: Royal Academy of Engineering.

Soares, A., Gomes, Á. & Antunes, C. H., 2014. Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions. *Renewable and Sustainable Energy Reviews,* Volume 30, pp. 490 - 503.

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,* Volume 44, pp. 576-583.

United Kingdom Hydrographic Office, 2014. *Her Majesty's Nautical Almanac Office.* [Online]
Available at: http://astro.ukho.gov.uk/psp/index_beta.html
[Accessed 19 August 2014].

University of Southampton, 2014a. *The role of community-based initiatives in energy saving.* [Online]
Available at: http://www.energy.soton.ac.uk/the-role-of-community-based-initiatives-in-energy-saving/
[Accessed 05 September 2014].

University of Southampton, 2014b. *Research project: Census 2022: Transforming Small Area Socio-Economic Indicators through 'Big Data'.* [Online]
Available at:
http://www.southampton.ac.uk/engineering/research/projects/census_2022_transforming_small_area_socio_economic_indicators.page
[Accessed 31 July 2014].

Walker, G., 2009. *The water and energy implications of bathing and showering behaviours and technologies,* London: Water Wise.

7. Appendices

7.1. Appendix A – Lighting Fixtures by Type

House ID	Standard	Low-Energy	% Low Energy
1	-	-	32%*
8	8	21	72%
9	-	-	32%*
10	28	9	24%
14	32	8	20%
15	11	9	45%
16	27	3	10%
18	34	16	32%
19	31	3	9%
20	11	9	45%
			32%

7.2. Appendix B – Tumble Dryer Power Consumption Data

Brand	Model	Energy consumption per cycle (kWh)	Cycle duration (minutes)	Power (kW)
BOSCH	WTE84301GB	4.2	124	2.0
ZANUSSI	ZDEB47209W	3.9	65	3.6
HOOVER	VTC671B	4.2	141	1.8
MIELE	T8722	3.8	111	2.1

7.3. Appendix C – Time Periods Used to Determine Cold Appliance Parameters

Hubid	Number of cold appliances	Date	Start time	End time
1	2	21/10/2011	00:00:00	08:00:00
3	2	08/10/2011	00:00:00	08:00:00
8	1	12/10/2011	08:00:00	12:00:00
9	1	16/10/2011	03:00:00	06:00:00
10	1	08/10/2011	01:00:00	06:00:00
11	1	21/10/2011	00:00:00	06:00:00
12	2	18/10/2011	00:00:00	23:00:00
14	2	08/10/2011	00:00:00	06:00:00
15	1	09/10/2011	01:00:00	06:00:00
16	1	07/10/2011	00:00:00	06:00:00
18	1	21/10/2011	01:00:00	06:00:00
19	2	08/10/2011	00:00:00	06:00:00
20	1	08/10/2011	00:00:00	01:00:00
21	1	08/10/2011	00:00:00	06:00:00
22	1	02/10/2011	00:00:00	06:00:00
26	1	08/10/2011	00:00:00	06:00:00
27	1	08/10/2011	00:00:00	06:00:00
29	1	08/10/2011	00:00:00	06:00:00

30	1	16/10/2011	00:00:00	06:00:00
31	1	21/10/2011	01:00:00	06:00:00
37	1	21/10/2011	01:00:00	03:00:00
38	1	21/10/2011	01:00:00	03:00:00
39	1	17/10/2011	00:00:00	06:00:00
41	1	17/10/2011	00:00:00	06:00:00
43	1	10/10/2011	03:00:00	06:00:00
44	1	10/10/2011	01:00:00	06:00:00
46	1	08/10/2011	02:00:00	06:00:00
48	1	08/10/2011	00:00:00	06:00:00
49	1	12/10/2011	00:00:00	03:00:00
50	1	12/10/2011	00:00:00	03:00:00
51	1	08/10/2011	00:00:00	06:00:00
53	1	18/10/2011	00:00:00	06:00:00
54	1	21/10/2011	00:00:00	06:00:00
57	1	12/10/2011	00:00:00	03:00:00
60	1	10/10/2011	00:00:00	06:00:00
63	1	21/10/2011	00:00:00	06:00:00
101	1	12/10/2011	00:00:00	03:00:00
104	1	08/10/2011	00:00:00	06:00:00
106	1	12/10/2011	00:00:00	03:00:00
107	1	12/10/2011	00:00:00	03:00:00
108	1	12/10/2011	02:00:00	06:00:00
109	1	10/10/2011	00:00:00	06:00:00
112	1	07/10/2011	00:00:00	06:00:00
115	1	01/10/2011	00:00:00	06:00:00
116	1	12/10/2011	00:00:00	03:00:00
117	1	08/10/2011	00:00:00	06:00:00
118	1	08/10/2011	00:00:00	06:00:00
119	1	08/10/2011	00:00:00	06:00:00
120	2	10/10/2011	08:00:00	16:00:00
123	1	08/10/2011	00:00:00	06:00:00
127	1	12/10/2011	00:00:00	03:00:00

7.4. Appendix D – Calculation of Theoretical Cold Appliance Load

	Short cycle				Long cycle				Total
hubid	Time ON (mins)	Time OFF (mins)	Power (W)	Continuous power (W)	Time ON (mins)	Time OFF (mins)	Power (W)	Continuous Power (W)	Continuous Power (W)
1	8	7	88	46.9	20	40	65	21.7	68.6
3	20	22	32	15.2	9	96	85	7.3	22.5
8	40	43	80	38.6	na	na	na	0.0	38.6
9	20	42	160	51.6	na	na	na	0.0	51.6
10	9	17	440	152.3	na	na	na	0.0	152.3
11	25	25	40	20.0	na	na	na	0.0	20.0
12	45	25	70	45.0	250	220	260	138.3	183.3
14	7	5	23	13.4	15	40	64	17.5	30.9
15	23	48	100	32.4	na	na	na	0.0	32.4
16	25	80	150	35.7	na	na	na	0.0	35.7
18	15	20	80	34.3	na	na	na	0.0	34.3
19	8	13	87	33.1	46	158	55	12.4	45.5
20	4	4	52	26.0	na	na	na	0.0	26.0
21	13	11	200	108.3	na	na	na	0.0	108.3
22	120	103	225	121.1	na	na	na	0.0	121.1
26	15	47	140	33.9	na	na	na	0.0	33.9
27	58	78	212	90.4	na	na	na	0.0	90.4
29	33	42	64	28.2	na	na	na	0.0	28.2
30	10	10	60	30.0	na	na	na	0.0	30.0
31	43	58	145	61.7	na	na	na	0.0	61.7
37	2	5	320	91.4	na	na	na	0.0	91.4
38	13	25	47	16.1	na	na	na	0.0	16.1
39	19	58	143	35.3	na	na	na	0.0	35.3
41	19	28	45	18.2	na	na	na	0.0	18.2

43	56	73	207	89.9	na	na	na	0.0	89.9
44	22	45	107	35.1	na	na	na	0.0	35.1
46	30	32	72	34.8	na	na	na	0.0	34.8
48	8	23	61	15.7	na	na	na	0.0	15.7
49	22	32	18	7.3	na	na	na	0.0	7.3
50	15	15	175	87.5	na	na	na	0.0	87.5
51	15	15	70	35.0	na	na	na	0.0	35.0
53	24	45	72	25.0	na	na	na	0.0	25.0
54	54	86	50	19.3	na	na	na	0.0	19.3
57	27	29	60	28.9	na	na	na	0.0	28.9
60	40	73	155	54.9	na	na	na	0.0	54.9
63	25	7	260	203.1	na	na	na	0.0	203.1
101	13	36	140	37.1	na	na	na	0.0	37.1
104	28	10	80	58.9	na	na	na	0.0	58.9
106	8	27	280	64.0	na	na	na	0.0	64.0
107	21	36	78	28.7	na	na	na	0.0	28.7
108	14	46	140	32.7	na	na	na	0.0	32.7
109	30	44	135	54.7	na	na	na	0.0	54.7
112	12	19	135	52.3	na	na	na	0.0	52.3
115	30	45	200	80.0	na	na	na	0.0	80.0
116	30	30	200	100.0	na	na	na	0.0	100.0
117	25	65	45	12.5	na	na	na	0.0	12.5
118	15	23	66	26.1	na	na	na	0.0	26.1
119	33	70	140	44.9	na	na	na	0.0	44.9
120	7	23	60	14.0	78	50	100	60.9	74.9
123	20	20	240	120.0	na	na	na	0.0	120.0
127	4	6	63	25.2	na	na	na	0.0	25.2

7.5. Appendix E – Modern Fridge-Freezer Power Consumption Data

Brand	Model	Energy Consumption (kWh/year)	Power ($W_{continuous}$)
BEKO	CXFD5104W	295	33.7
SAMSUNG	RL58GPEIH	268	30.6
LOGIK	LFC50S12	226	25.8
HOTPOINT	FFU4DX	377	43.0