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Stochastic bottom-up modelling of household appliance usage to quantify the demand response potential in UK residential sector

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Stochastic Bottom-up Modelling of Household Appliance Usage to Quantify the Demand Response Potential in UK Residential Sector

Declaration

I, Selin Yilmaz, confirm that the work presented in this thesis is my own.

Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed:

(February 2017)

Abstract

This thesis presents the development of a new, stochastic bottom-up model for predicting household appliance energy demand, named the Household Appliance Usage (HAU) model. Three sub models are developed which have different functions and are based on different supporting datasets. Firstly, 2013-2014 English Housing Survey (EHS), a UK Government national representative household sample of around 17,000 homes, is chosen to provide a platform to generate the electricity demand profiles. Secondly, an appliance ownership model is developed where the nationally representative household sample is populated with electrical appliances using the appliance saturation levels derived from 2011 UK Government's Energy Follow-Up Survey (EFUS) of 3000 homes. Thirdly, an occupant behaviour model is developed where appliance behaviour metrics are simulated using monitored data from the UK Government's 2011 Household Electricity Survey (HES) of 225 homes, and electricity demand profiles are generated using the results of the appliance behaviour model.

A new approach to bottom-up occupant behaviour modelling for predicting the use of household electrical appliances in domestic buildings is presented. Stochastic model predictions are made for individual households and appliances which can be used as inputs for the dynamic thermal simulation of buildings. Three metrics relating to appliance occupant behaviours are defined: the number of switch-on events per day, the switch-on times, and the duration of each appliance usage. The metrics were calculated for 1,076 appliances in 225 households in the HES sample. The analysis shows that occupant behaviour varies substantially between households, across appliance types and over time. This new modelling approach uses probability and cumulative distribution functions to capture daily variations and is based on individual households and appliances. It is shown to have advantages for modelling the variations in appliance occupant behaviours.

Two minutely household appliance electricity demand profiles are generated using the appliance behaviour metrics and power demand during usage. The comparison of simulation results and measured values show that the HAU model daily power demand predictions closely match the measured data (up to 8% difference during peak time).

The final HAU (Household Appliance Usage) model, which generates aggregate electricity demand profiles of 13,276 households that were randomly populated with appliances for 16 appliance types, is scaled up to national level using the weighting factors calculated by the 2013-2014 EHS study.

The HAU model is then applied to demand shifting of individual appliance in the households to evaluate the extent that electricity demand could be shaped by time shifting. The findings provide insights about the amount of residential load that is available for shifting and a discussion is presented on the future potential of household electricity demand response. The implications of findings for policy, industry and research are discussed. The thesis discusses the design of future monitoring studies (including monitoring strategies and sample sizes) and the design of future research studies (including statistical analysis, probabilistic modelling and validation approaches) in order to further improve our understanding of and ability to predict the behaviours of occupants and their use of household appliances within buildings.

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Acknowledgments

- I gratefully acknowledge the Engineering and Physical Sciences Research Council, as principal funder of this research through support for the London-Loughborough Centre for Doctoral Research in Energy Demand, grant number EP/H009612/1.
- Very special thanks to my supervisors Steven Firth, David Allinson for being so exceptionally ready to discuss ideas, make suggestions and give constructive feedback.
- Very special thanks to Prof. Kevin Lomas for his insightful guidance, experience and critical appraisal of my research have been extremely valuable beyond the course of this PhD.
- Very special thanks to the members of IEA Annex 66 for their constructive feedback.
- My colleagues at LoLo Centre both at Loughborough University and UCL Energy Institute who have contributed to this work with ideas and support.
- I must thank my family, sisters and my cats and most of all Jonathan my partner in crime for their amazing support over the past few years.
- Very special thanks to Karen Holmes who helped me organise the conference trips and literally everything else so perfectly, and always there to help me whenever I had any problems.

Finally, I would like to dedicate this thesis to my grandma (γιαγιά) who encouraged her daughters, grand-children and children of grand-children to science and to Karen Holmes who was very helpful through my PhD...

Previously published work

- Yilmaz, S.; Firth, S.K.; Allinson, D. (2017). Occupant behaviour modelling in domestic buildings: the case of household electrical appliances. Journal of Building Performance Simulation. doi: 10.1080/19401493.2017.1287775
- Yilmaz, S.; Firth, S.K.; Allinson, D. (2015). A novel methodology for generating residential buildings electricity demand profiles. In Proceedings of International Building Physics and Simulation Association, pp 656- 663. Hyderabad India.
- Yilmaz, S.; Firth, S.K.; Allinson, D. (2015). Developing a modelling framework to quantify the demand response potential of domestic appliances in UK homes. In Proceedings of 8th International Conference on Energy Efficiency in Domestic Appliances and Lighting, pp 1339-1351. Lucern, Switzerland.

List of acronyms

ANOVA	Analysis of variance
BEIS	Business, Energy & Industrial Strategy
BRE	Building Research Establishment
BREDEM	Building Research Establishment Domestic Energy Model
CDF	Cumulative Distribution Function
CSV	Comma Separated Value
DECC	Department of Energy and Climate Change (United Kingdom)
EFUS	Energy Follow Up Survey
EHS	English Housing Survey
ENA	Energy Networks Association
EPSRC	Engineering and Physical Sciences Research Council
GB	Great Britain
HAU	Household Appliance Usage
HES	Household Electricity Survey
ICF	Inner City Fund
IEA	International Energy Agency
PDF	Probability Density Function
TOU	Time of Use
UK	United Kingdom
US	United States (of America)

1 INTRODUCTION

This chapter briefly sets the scene and presents relevant background information against which this study positions itself. The main research question is defined and aims and objectives are laid out. The main structure of the thesis is briefly outlined to provide the reader with guidance for subsequent reading.

1.1 UK ELECTRICITY SECTOR AND DEMAND RESPONSE

The UK electricity sector will undergo a significant change as part of the transition to a low-carbon economy over the coming decades. The UK Government is committed to developing a low carbon economy and to meeting the 15% renewable energy target by 2020 and the 80% carbon reduction target by 2050 (HM Government, 2011). The centralized electricity generation system currently based on largely fossil fuels is likely to be replaced by a combination of nuclear, carbon capture and storage (CCS) and renewable generation. There is a significant degree of uncertainty as to which of these technologies will become dominant (UKERC, 2013). Incorporating renewable energy generation would involve the widespread use of wind, solar, biomass and tidal energy. Wind is already gaining a high share as part of a mix of low carbon generation with more capacity in development. By 2050, wind power could supply more than half of the annual electricity demand (DECC, 2010a). Solar photovoltaics (PV) are also expected to be an important part of the low carbon energy system, showing a strong growth in the installed capacity at the domestic level since the introduction of the Feed-In Tariffs (DECC, 2011).

On the demand side, considerable growth is expected in the use of electric heating and vehicles, again resulting from the need to move away from carbon intensive fuels (DECC, 2011, 2015a). If this happens, the UK in 2050 will have higher demand for electricity than today paired with a less flexible supply. The shape of the daily domestic electricity demand profile (the variation in the electricity demand across a day) is also likely to change (DECC, 2010a). Currently, the national mean domestic demand profile

indicates a profile which has a slightly higher demand in the morning (morning peak demand) and a higher demand in the evening (evening demand peak) (Figure 1.1).

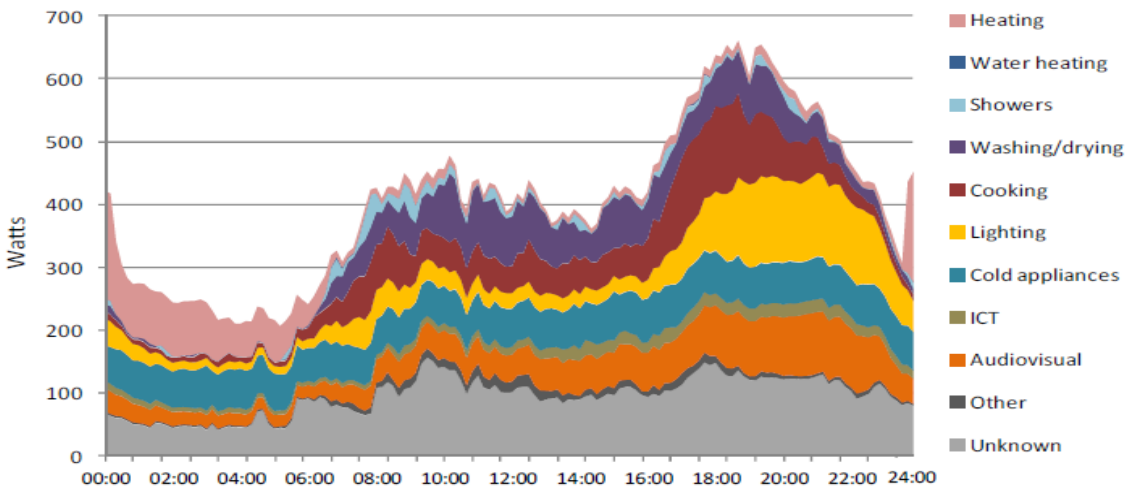


Figure 1.1 Average demand of domestic appliances in the UK as estimated by Household Electricity Use Survey (DECC, 2013a)

However, due to the electrification of transportation, domestic charging demand for electrical vehicles would likely increase the magnitude of peak demand in the evening and late at night (Richardson, 2010; Strbac et al. 2010). Similarly, heat pumps may add significantly to the morning peak demand (Torriti, 2011).

One of the key characteristics of the electric power system is that electricity cannot be stored economically at a very large scale. Therefore, the electricity supply and demand must be balanced in the system. Traditionally, conventional power plants follow the demand which is the sum of the requirements of all consumers connected to the power grid. They are called upon to generate electricity according to foreseeable demand fluctuations in form of yearly (summer vs. winter), weekly (working day vs. weekend) and daily (night vs. daytime) variations (Lorubio, 2011). This method of demand and supply balancing has worked to date as there has been relatively little intermittency in power sources. However, demand-supply balancing in electricity grids becomes a more sophisticated problem by the increased time-varying, less predictable, and less controllable supply side. This is due to the increasing share of intermittent renewable technologies and less flexible nuclear and carbon capture and storage plants. The

output of renewable generation (such as wind and photovoltaics) varies with weather conditions and it is difficult to modulate the output of renewables to follow a particular demand shape. Nuclear power is relatively inflexible compared to fossil fuels, and is most optimally run at constant output (Freris et al. 2008).

Due to intermittency, the probability that renewable power can contribute towards meeting the peak demands is considerably lower than it is for traditional fossil-fuel plants (McKenna, 2013). Additionally, renewable power generation fluctuations may happen quite rapidly due to changes in meteorological conditions, disturbing the stability of the frequency of electricity. For both cases, this may require continuation of emission intensive power stations which are incompatible with the carbon targets to provide balancing and capacity reserve. Challenges for system balancing may also arise as the grid becomes overloaded by renewable power generation with not enough demand on the system to make use of it. In this case, renewable power generation would need to be constrained and constraint payments would be required for the lost generation (Scottish Government, 2013). Furthermore, the surplus electricity from solar photovoltaics can potentially increase the voltage of the local electricity distribution system beyond the regulated voltage level and utilities may need to install expensive voltage regulating devices (Fujimoto et al. 2011; Bhartiya et al. 2012).

To tackle the challenges mentioned above for system balancing, there is a considerable interest in storage of the excess power generation to be used later (Black and Strbac, 2007; Committee on Climate Change, 2008) and the incorporation of demand flexibility to reduce the need for storage or back-up generation (National Grid, 2009; Ofgem, 2010; IEA, 2011). Of these, demand flexibility is increasingly recognized as the less capital intensive approach to help system balancing (Fischer 2008; EPRI 2009; Gottwatt et al. 2011). Demand flexibility is referred to as the possibility to change (adapt, deviate, shift) the electricity consumption profile with the aim of better demand and supply matching. Therefore, demand flexibility is directly related to the deployment of demand side response (UKERC, 2014). 'Demand response' refers to flexible demand where consumers time-shift demand, either through behaviour change or automation, in response to particular conditions within the electricity system (Ofgem, 2010; Owen and Ward, 2010; Torriti et al., 2010).

The UK residential sector represented 27.2% of total UK final energy consumption in 2015 (BEIS, 2016a). Domestic appliances including lighting represented 32.2% of the total energy demand and 73.1% of the total electricity demand of the domestic sector in 2015 (BEIS, 2016b). As a result, home appliances are one of the key instruments to provide demand flexibility. (Strbac et al, 2010; National Action Plan for Energy Efficiency, 2010; European Commission, 2013). The residential sector can offer flexibility in which households take a significant active role by adapting their behaviours or shifting the timing of certain appliances in periods when electricity is relatively cheap or available in abundance, therefore enabling better match of demand and supply. There is relatively little flexible demand that has been secured in the residential sector (Ofgem, 2010). A recent survey of studies on demand response shows that smart appliances (appliances capable of responding to system changes) and enabling infrastructure significantly improve the responsiveness of consumers to system changes (Faruqui et al., 2013). With the increasing deployment of smart metering and smart appliances, the smart system can adjust the operation of smart appliances according to the information provided by suppliers, therefore the participation of the private households can be strongly enhanced with the availability of two-way communication (Ehrhardt-Martinez et al. 2010). Smart meter technology is slowly rolling out in the UK through trials (with every home is to be fitted with one by 2020), bringing the potential for automated load management in the future.

There is a common perception that there exists a significant scope for demand shifting to provide benefit to future electricity system operations with low carbon technologies (US DOE, 2006; Strbac et al. 2010; ENA and Energy UK, 2012). Previous studies have developed models that investigate the effects of demand response (Paatero and Lund 2006, Fujimoto et al., 2011; Widén et al., 2012). Trials have been also tested by electricity utilities for the residential sector to measure the effectiveness of the demand response techniques (EFFLOCOM Partners, 2004; Frontier Economics and Sustainability First, 2012; Suzenksi, 2012).

1.2 HOUSEHOLD APPLIANCE ELECTRICITY DEMAND MODELS

One approach to understanding and quantifying the demand flexibility and potential of demand response in the residential sector is through using energy demand models. Currently, occupants interacting with appliances in building simulation tools are represented in terms of fixed static schedules (Hoes et al., 2009). Simulation tools such as DOE-2, BLAST and EnergyPlus typically use one average profile per appliance based on a library of typical profiles such as residential or office work. The values of the profile are multiplied by the installed power of each appliance type (Abushakra and Claridge, 2001). However, such procedures can lead to overestimated peak values, as defining standard behaviour for types of households fails to consider the random variability of the occupant behaviour (Tanimoto and Hagishima, 2010). Moreover, considering the occupant behaviour variation may be advantageous with regards to instantaneous electricity demand since certain systems must be sized to meet the maximum expected simultaneous load (Yao and Steemers, 2005; Widén and Karlsson, 2010) and may underestimate the problem of grid instability (Baetens and Saelens, 2011). This issue has also received considerable attention in zero carbon buildings (Hoes et al., 2009; Salom et al., 2011). Researchers have developed a number of stochastic bottom-up appliance use models to integrate with simulation tools in order to include the randomness linked to the variation in occupant behaviour between households and the variation in time of each behaviour. Typical datasets used to develop appliance use models are Time of Use (TOU) datasets based on one-day diaries reporting households' daily activities of 5,000 to 10,000 households (Tanimoto et al., 2008; Richardson et al., 2010; Widén et al., 2012, Wilké et al., 2013). There are also long-term observational studies where appliances were monitored for extended periods using electrical power sensors (Page, 2007; Tabak and de Vries, 2010). The studies that used TOU data obtained the switch-on times and duration of appliance use from user diaries and then estimate the appliance power demands with fixed power demand (pre-defined power demand for appliance operation). The occupancy behaviour patterns associated with different types of households and days are analysed to develop these models. In this approach, the switch-on times cannot be identified precisely as users write down their daily activities each 10 or 15 minutes. One-day diary based TOU datasets can also fail to capture the

difference in behaviour for an extended period of time because they only recorded data up to two days (one weekday and one weekend). For example, the variation in durations/choice of programme between usages within the same household cannot be captured. Other studies analyse the measured sensor data to obtain the switch-on times, duration and the power demand profiles (Page, 2007; Tabak and de Vries, 2010). The limitation of these studies is that as monitoring is expensive, long-term studies in the literature typically only contain information relating to a small sample size (2 to 10 homes); thus they cannot be considered representative of the wider housing stock and are not able to capture behavioural diversity among different household groups.

To address these limitations, this thesis describes the construction and validation of a comprehensive and realistic household appliance electricity demand model in order to provide a bottom-up assessment of demand flexibility comprehensively and quantitatively. This thesis develops new insights into occupant behaviour modelling for household electrical appliances used by studying the development and application of different modelling techniques to one of the most comprehensive datasets of household appliance usage recorded to date: the UK Government's 'Household Electricity Survey' (HES) (DECC, 2014a). Furthermore, the study intends to provide insights into to the demand flexibility of the UK residential sector in order to provide a bottom-up assessment of demand flexibility comprehensively and quantitatively for demand response opportunities.

1.3 RESEARCH QUESTIONS

In order to address the challenges described in Section 1.1 and Section 1.2 raised by the literature review, this study sets out to answer the following research questions:

1- What is the best approach to model the occupant behaviour of appliance use for demand response studies?

Several methods have been used to model the appliance usage and the domestic appliance electricity demand profiles for better prediction of time variations of the demand and the peak power demand. Which appropriate characteristics should the model have for better accuracy, or capability to show daily variations to reflect the changing level of demand and to simulate large numbers of dwellings, therefore be computationally efficient? Can the existing methods be improved upon by offering novel approaches? Which is the most ideal approach with the purpose of forming a basis upon which quantifying the effect of individual appliance shifting on the household appliance electricity demand profiles can be studied? This research question is addressed in Chapter 4 and Chapter 5.

2- To what extent can the residential sector electricity demand be shaped with demand response (shifting the time of the demand)?

The flexibility that can be offered by the home electric appliances can be different due to different usage patterns, runtime, power demand, operational constraints and advantages. Therefore, it is necessary to assess the sources of flexible demand in the houses and the extent of flexibility that the utilities can expect from the households in order to provide insights that would contribute to peak demand reduction and demand and supply balancing. This research question is addressed in Chapter 6.

1.4 AIM AND OBJECTIVES

The overall aim of this thesis is:

To investigate a bottom-up stochastic household appliance electricity demand modelling and its application to improve the understanding of the demand response potential in the UK residential sector

A household appliance usage (HAU) model will be developed that generates 24-hour (daily) electricity demand profiles for a large sample of UK homes. The study will use one of the most comprehensive datasets of household appliance usage recorded to date: the UK Government's 'Household Electricity Survey' (HES) (DECC, 2014a). The HES took place in 2011 and, for periods of either one month or one year, recorded the electricity consumption of 5,860 household electrical appliances in 251 homes. The study intends to explore the potential of demand response in the UK residential sector and provide insights to the flexibility of the household electricity demand that could be of interest for the peak demand reduction and demand and supply balance issues.

This aim is achieved by meeting the following six research objectives:

- *Objective 1: To conduct literature review on the occupant behaviour of appliance use and existing modelling techniques*

Firstly, the review of available literature on the UK residential electricity consumption trends, concepts and definitions of demand flexibility and demand response will be presented along with policies developed for demand response implementations. Secondly, factors such as appliance ownership and appliance usage patterns that affect the electricity demand in homes and demand response potential will be discussed and evidence from literature will be provided. Metrics relating to appliance and occupant behaviours will be defined. Lastly, Research Question 1 is partly addressed in Chapter 2 by conducting a review, analysing the studies in the past that have proposed electricity demand models and demand response simulations in the residential sector to analyse strength and limitations of the current electricity demand models and to therefore identify and compare the characteristics and scope of the models, modelled appliances and end-uses covered by the models.

- *Objective 2: To study the HES dataset to identify appliance usage patterns and electricity use by households*

A thorough data analysis of the HES dataset will be done in Section 4.5 and Section 5.2 to identify and calculate the occupant and appliance behaviour metrics for appliance use chosen for this study for each appliance type. In addition, the electricity consumption and daily power demand profiles will be calculated as well as the appliance characteristics regarding the power demand during appliance use.

- *Objective 3: To develop a household appliance usage (HAU) model that generates household electricity demand profiles*

A bottom-up stochastic model will be developed that generates daily electricity demand profiles on an appliance basis and then aggregates these to create household electricity demand profiles (explained in details in Chapter 3, mainly in Section 3.5). The model will simulate home appliance electricity demand at 2-minute time resolution that includes important features of home appliance electricity demand such as diurnal variations and short term fluctuations. The aggregate electricity demand profiles of the households that are randomly populated with appliances for 16 appliance types will be simulated and scaled up to national level using weighting factors (presented in Section 3.7).

- *Objective 4: To validate the model*

The developed model will be validated against the actual demand data. The aim with the validation of the model is to check the ability of the HAU model to recreate the patterns observed in the monitored dataset. The validation will be done on developed metric levels as well as on appliance level and aggregate level presented in Section 4.3 and Section 5.3). The simulation results will also be compared with national statistics (Section 6.3).

- *Objective 5: To generate the aggregate electricity demands of households and quantify the potential for demand response*

The aggregate daily electricity demand profiles of the households that are randomly populated with appliances will be simulated. The HAU model will then be used to quantify the demand response potential for the major household appliances (Section 6.4). This will be done through time-shifting of individual appliances to a different time of the day and calculate the changes in the daily electricity demand profiles to identify how much flexibility can be offered by shifting these major appliances.

- *Objective 6: To discuss and indicate the possible implications for policy makers, academia and electricity utilities*

The developed HAU model will be the main output of this research, alongside the quantification of demand response in the UK residential sector (Chapter 7). It is expected that the results of this work will interest electricity distribution utilities and system operators who need to balance demand and supply in low carbon systems by providing an insight into the potential of demand response available in the UK residential sector. Moreover, particular results such as the amount of flexible demand in the UK's residential sector will be of interest to market retailers who consider proposing dynamic pricing based on demand response. The study will provide possible implications for policy-makers and aggregators of demand response resources.

1.5 THESIS STRUCTURE

This thesis has eight chapters. The chapters that follow this introduction are outlined below.

Chapter 2. Literature review

This chapter firstly presents a review of residential electricity consumption trends for appliances in the UK. Then appliance factors which influence the household electricity demand that were identified by previous studies are presented in details. The review includes specific occupant behaviours that previous authors have linked to household electricity demand and provides a state-of-the-art of appliance electricity modelling.

Chapter 3. Methods

This chapter outlines the methods applied in this thesis to meet the aim and objectives to answer the research questions. This includes descriptions of research design and research methods used, as well as methods of data collection. This is followed by an account of the stages of data processing and methods of data analysis. The modelling method for household appliance usage (HAU) model is presented. Finally, the method for applying the household appliance usage (HAU) model for quantifying the demand response potential in the UK residential sector is explained.

Chapter 4. Result #1: Appliance Behaviour Modelling

This chapter presents the data analysis to calculate the appliance behaviours from the monitored HES dataset. It includes the analysis of variation in appliance behaviours for different household groups. Later, the simulation results of the HAU model with different modelling approaches are presented for each appliance behaviour and appliance type and compared with the monitored HES dataset.

Chapter 5. Result #2: Power Demand Modelling

This chapter presents the data analysis to calculate the electricity consumption and daily power demand profiles of the households in the HES dataset. Appliance characteristics regarding the power demand during appliance use are identified. Lastly, the HAU model is validated on appliance level and on aggregate level by comparing the average daily power demand profiles of the HAU model simulation results with the monitored dataset.

Chapter 6. Result #3: Application of the HAU Model for Demand Response Potential

This chapter firstly presents the simulation results and the validation of the appliance ownership model developed. The aggregate electricity demand profiles of 13,276 households that are randomly populated with appliances for 16 appliance types are simulated and scaled up to national level using the weighting factors. The simulation results are compared with national statistics. Finally, the HAU model is applied to quantify and provide further evidence of demand response potential in the UK residential.

Chapter 7. Discussions

This chapter discusses the current research findings with respect to previous research and describes potential implications for modelling occupant behaviour of appliance use and policies aimed at demand response studies for the UK residential sector.

Chapter 8. Conclusions

This chapter presents a summary of key findings from the research and a discussion of the contributions to knowledge. Limitations of the current research are highlighted and potential areas of future research are identified.

2 LITERATURE REVIEW

This chapter begins by showing the trends of UK residential energy consumption, focusing particularly on the use of electrical appliances. After an initial review of research into demand side management, the concepts of “demand flexibility” and “demand response” are defined. Consideration is then given to the role of appliances and factors which affect the household electricity demand and demand flexibility. It also reviews studies that have developed appliance electricity demand models, leading to a discussion of theories and models which have been used to construct the electricity demand models. The chapter ends with a review of demand response modelling studies.

2.1 RESIDENTIAL ELECTRICITY CONSUMPTION TRENDS

This section aims to provide a brief overview of the trends of energy consumption of the residential sector in the UK since 1970 with a focus on the present status of electricity consumption.

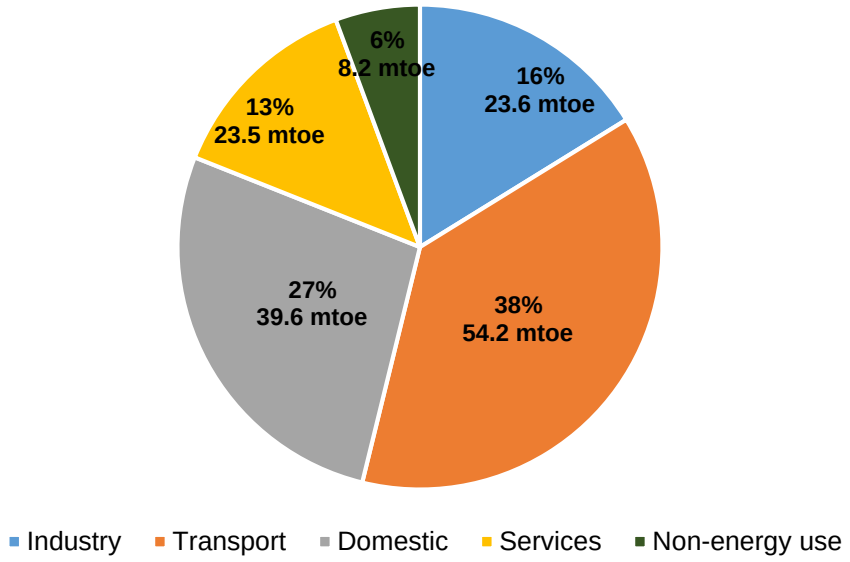


Figure 2.1 Proportion of final consumption in mtoe (million tonnes of oil equivalent) of UK energy divided into sectors Source: BEIS, 2016

UK Government energy statistics show the total final energy consumption of different sectors for 2015 as shown in Figure 2.1. The residential sector has the second largest proportion of energy consumption after transport, and represents 27% of total UK final energy consumption. Industry and services represent 16% and 13%, respectively whereas non-energy (energy products such as solvents and road making materials) represent 6% of the UK final energy consumption.

The UK Housing Energy Fact File published by DECC (2014a) gives the domestic end-use energy consumption data from 1970 to 2012. The data from the English Housing Survey (DECC, 2014b) has been modelled using BREHOMES and the Cambridge Housing Model (CHM). The data includes the energy used for space heating, hot water and cooking as well as appliance energy consumption. The report suggests that since 1970, there has been a continued fall in the proportion of energy used for water heating and cooking, and a continued rise in the proportion used for lighting and appliances. Space heating remained the primary use of energy in the home over the whole period. Tables in Energy Consumption in the UK where the data sourced from DUKES (DECC, 2013c) supports this argument. Figure 2.2 shows the final residential energy consumption by end use in the UK from the DUKES data; 65.6% of domestic energy use was from space heating, 16.4% from water heating, 15.4% from lighting and appliances, and 2.6% from cooking appliances in 2012.

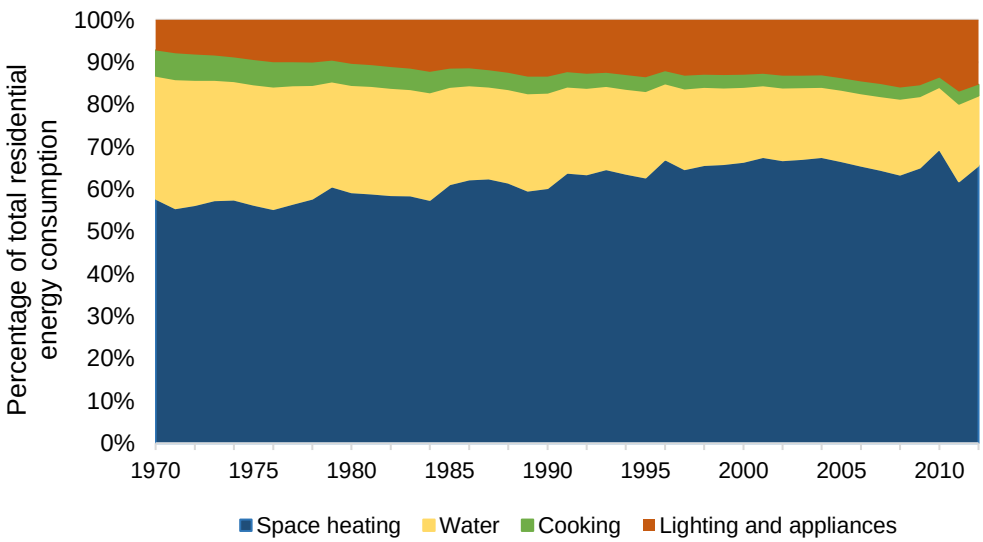


Figure 2.2 Domestic final energy consumption by end use, UK (1970 to 2012), Source: DECC, ECUK Table 3.04

Appliances' share of total energy use in homes has increased significantly whereby household appliances used less than 7% of total energy in 1970, and they now use nearly 17%. Appliances energy use has almost tripled in 40 years (DECC, 2013d).

The total energy use by fuel type and end-use based on the outputs of the Cambridge Housing Model suggests that the total amount of electricity consumption by home appliances grew by around 18% over 20 years; and lighting and appliances' share of total electricity use has changed between 63% and 71%. In 2012, lighting and appliances' share of total electricity use was 67% whereas space heating, water heating and cooking represented 21.3%, 6.6% and 5.1% of the total electricity consumption respectively (DECC, 2013e).

Figure 2.3 shows the trends of appliance types used in the UK from 1970 to 2012 based on data provided by the Market Transformation Programme (MTP) through sales figures and scaled to DUKES total figures (DECC, 2013f). To examine the trends of electricity consumption by home appliances and lighting in more detail, the appliances are categorized into five types. Cold appliances are composed of fridges and freezers; wet appliances are washing machines, dishwashers, tumble dryers; consumer electronics include TVs, set top boxes, DVD/VCRs, game consoles and power supply units; home computing is composed of desktops, laptops, monitors and printers; and finally cooking appliances are composed of electric ovens/hobs, microwaves and kettles. Lighting includes light bulbs, halogen and fluorescent lights, energy saving light bulbs and LEDs.

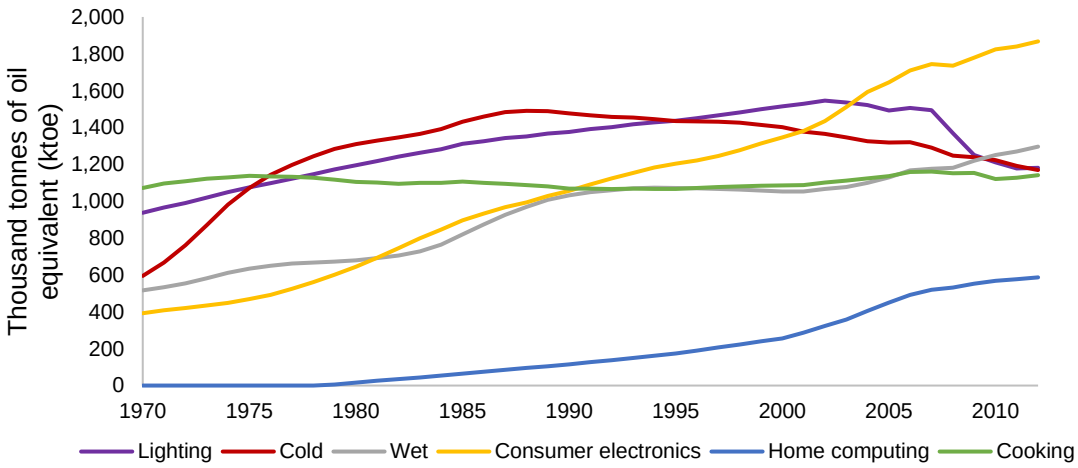


Figure 2.3: Electricity consumption by home appliances in the UK (1970 to 2012). Source: DECC, ECUK Table 3.10

As can be seen from Figure 2.3, between 1970 and 2012, electricity consumption from consumer electronics and cold appliances has increased by 376% and 151%, respectively. Although cold appliances usage has increased by 151% since 1970, there has been a decrease since 1986. Consumer electronics were the largest consuming domestic appliances group with an estimated consumption of 1,868 ktoe, followed by wet appliances with an estimated consumption of 1,296 ktoe, lighting with an estimated consumption of 1,181 ktoe and home computing rose to 587 ktoe in 2012.

Another important aspect of electricity demand for home appliances is the variation of the power demand throughout the day. Figure 2.4 shows the demand profile of an average UK household constructed from different appliance categories. This graph is developed using the power measurements from the datasets of household appliance usage recorded by the UK Government's 'Household Electricity Survey' (HES) (DECC, 2014a). The HES took place in 2011 and, for periods of either one month or one year, recorded the electricity consumption of 5,860 household electrical appliances in 251 homes. Figure 2.4 highlights the differences that occur in appliance usage across appliance categories and appliance types. It shows that different appliances are used at different times of the day. Cooking appliances are used around morning, noon and evening times which are presumably meal times. Peak time occurs in the morning and evening for washing/drying. Cold appliances have nearly constant demand throughout the day. ICT are in use throughout the day, however increases start from the morning and peak times occur in the evening. Peak time occurs in the morning for electric showers.

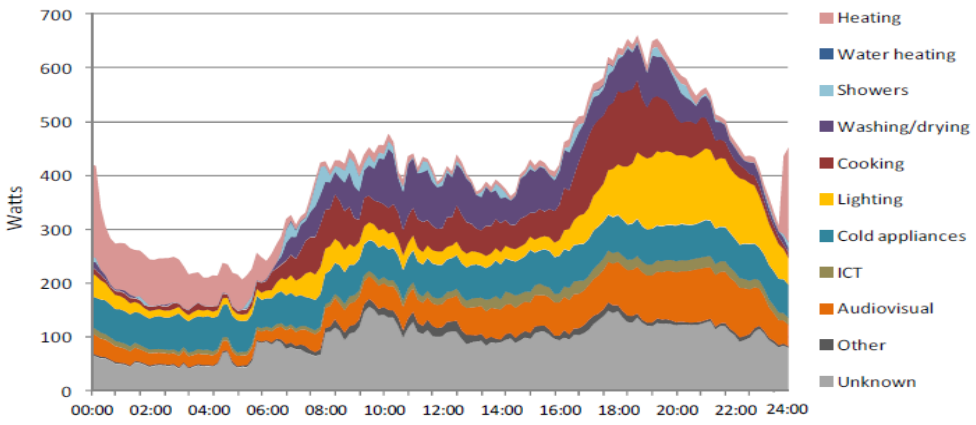


Figure 2.4 Average demand of domestic appliances in the UK as estimated by Household Electricity Survey (DECC, 2013a)

2.2 DEMAND FLEXIBILITY AND DEMAND RESPONSE

2.2.1 Demand flexibility

As mentioned in Section 1.2, the future energy systems paradigm implies incorporating energy demand flexibility of buildings into smart energy systems to cope with the stochastic behaviour of renewable energy sources. Many authors have studied demand response and control strategies; however, they rarely define energy demand flexibility nor present a general methodology to assess the flexibility. Ofgem (2016) defines flexibility as 'modifying generation and/or consumption patterns in reaction to an external signal (such as a change in price) to provide a service within the energy system'. Several authors (Hidalgo González et al., 2015; Silva 2010; Ma, 2012) describe the term flexibility as the ability of a power system to adapt its operation to both predictable and unpredictable fluctuating conditions, while maintaining a satisfactory level of reliability at a reasonable cost, over different time horizons (Ma, 2012; Silva 2010). Although several studies have defined demand flexibility, any common metrics or indicators to quantify the amount of flexibility of a building are lacking. Six et al. (2011) simply defined the flexibility of an appliance (heat pumps at their study) as the number of hours the operation can be delayed. Belhomme et al., (2009) defined an hourly flexibility index which is calculated proportionally to the hourly load. The hourly load is computed according to the probability of use of the considered appliance during the day. Starke et al. (2013) defined a flexibility value for each hour, representing the fraction of load that is willing and able to participate in demand response at that hour. Gottwalt et al. (2011) defines the amount of flexible load as the amount of electric power shifted between the hours of the day and assesses the flexible load under variable prices. De Coninck and Helsen (2013) defined the flexibility as the possibility to deviate the electricity consumption from the business as usual consumption (a reference strategy that minimizes the electricity cost) at a certain point in time and during a certain time span. They used this metric to enable a quantitative comparison of the 'amount' of flexibility and corresponding cost between different buildings and groups of buildings. The definition of demand flexibility given as '*electric power which is shifted between the hours of the day*' (Gottwalt et al., 2011) was

selected as being specific enough to exclude interpretations which are not relevant to the questions posed in this study.

2.2.2 Demand response

Demand response was originally suggested by electric utilities in order to provide and increase the flexibility on the demand side by shifting or reducing peak energy demand, thereby avoiding costly energy procurements and capacity investments. Demand response is seen as an important part for providing a flexible energy system (Ofgem, 2016). Recently, governments and stakeholders are recognising that demand response is seen as an important part for providing a flexible energy demand in future energy systems (Committee on Climate Change, 2008; Ofgem, 2010). In literature different definitions are used for demand response.

The International Energy Agency (2003) defines the demand response as follows: “Demand response includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption”. Greening (2010) states that the demand response includes both modification of electricity consumption by consumers in response to price and the implementation of more energy efficient technologies.

The definitions mentioned above include energy savings. In several studies, demand response is defined with a boundary, focusing on the short-term responses such as the load management rather than the actions to reducing long-term energy and/or the capacity needs. Element Energy (2012) describes demand response as ‘change in electricity consumption patterns in response to a signal’. U.S. Department of Energy (2006) defines the demand response as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high prices or when system reliability is jeopardised”. Energy Networks Association (2014) has defined the demand response quite specifically as “a deliberate and dynamic change in electrical power demand in response to a specific signal (by the user or 3rd party) as seen by the electricity network (at 11kV and above)

from the demand that would otherwise have been expected". Torriti et al. (2010) indicates a similar definition: "the term "Demand Response" refers to a wide range of actions that can be taken at the customer side of the electricity meter in response to particular conditions within the electricity system (such as high prices)". The actions can be categorized as the participation of the households as a response to factors such as incentive pricing, new tariff schemes, greater awareness and an increased sense of responsibility, but their participation may involve either active behavioural changes or passive responses through the use of automation (ENA and Energy UK 2012). The definition of demand response given above as '*change in electricity consumption patterns in response to a signal*' (Element Energy, 2012) was selected as being specific enough to exclude interpretations which are not relevant to the research questions posed in this study. This study is concerned with appliance electricity demand profiles and interested in a range of approaches to demand response that may or may not be based on price signals, and does not take energy efficiency improvements as its focus. Demand response is considered to provide benefits to both electricity markets and technical system efficiency. A summary of the benefits of demand response are given in Table 2.1 and the challenges for delivering demand response are given in Table 2.2.

Table 2.1 Benefits offered by demand response

BENEFITS

Economic efficiency

- Reduce the peak-generation needs by smoothing the daily demand profile and shifting some of the demand that occurs at peak time to times of lower usage, therefore reducing the need for additional networks and the amount of generation capacity which will further reduce the transmission assets required to provide electric service (Faruqui and George, 2005).

System reliability

- Offer a greater degree of demand flexibility where demand can be scheduled to coincide with generation availability to increase intermittent renewable technologies (wind and solar power integration) integration.
- Help to resolve the issues of network voltage rise outside of the statutory limits by shifting the demand to coincide with peaks in high penetrations of micro-generation such as domestic solar photovoltaic (Thomson and Infield, 2007).
- Manage the additional demand in the future with higher load and peaks due to increased electrification of heat and transport in order to minimise the peaks in aggregated demand on the network (Strbac et al., 2010).

Environment

- Help to save emissions by reducing the need to use more costly and emissions-intensive plants during peak times as the plants with the highest running costs are used at times of peak demand and these plants often emit more carbon dioxide per unit of electricity generated than plants used at off-peak times (DECC 2012).

Table 2.2 Challenges identified for demand response applications

CHALLENGES
Network and Technology based: • Lack of technology to develop demand response system and required infrastructure. Advanced metering, communications, control methods and information technologies have been largely absent from electricity systems. • Lack of experience and considerable uncertainty in the context of demand response trials although the key ingredients of the technology exist.
Market based • Inappropriate market structure and lack of incentives for demand response therefore often not competitive when compared with traditional approaches when the generators or the retailers face financial risks caused by spot price volatility in the wholesale electricity market. • Decrease of governmental and utility funds to promote demand response policies since the beginning of the deregulation of the markets (Moreno et al., 2004).
Behaviour • Behavioural barriers such as households that are resistant to change in general, mainly due to comfort reasons. (McKenna, 2013).

2.2.3 Demand response in the UK domestic sector: status and potential

Demand response has been employed in various ways in Great Britain for decades. In the domestic sector the Economy 7 tariff, introduced in the 1970s, is one of the predominant demand response schemes. Customers are offered a lower rate per unit of electricity than the average unit rate for a period overnight and a higher rate during the day. It is designed to be used in combination with water heating and electric night storage heating. There is no centralized record of the number of households in the UK currently on a time of use tariff[1], but 17% of the electricity consumed in the UK in 2013 was reportedly purchased under some form of off-peak pricing structure (DECC, 2014a; Fell, 2016). Though such tariffs are not currently widely used in the UK, a number of trials have placed people on demand response tariffs to test whether they will change their energy consumption patterns[2].

[1] A contractual demand response arrangement in which the unit price for electricity varies over time, usually referred to as (TOU) tariffs.

[2] For a literature review of 30 trials, see, for example:"Demand Side Response in the domestic sector – a literature review of major trials", 2012. goo.gl/nufyV9

In the United Kingdom, the potential for an increased role for domestic demand response has gained significant recognition at policy level and with regulatory initiatives. Through the Smart Meter Implementation Programme, the Government hopes that every home and small business in Britain will get smart electricity and (where appropriate) gas meters by 2020 (DECC 2014c). During the Report Stage of a new legislative package, the Energy Bill, Lord Hunt of Kings Heath, stated that ‘‘I am pleased to announce that the Government has taken the decision to mandate smart meters for all households. This is a major step forward; no other country in the world has moved to an electricity and gas smart meter roll-out on this scale. The existing powers in the Energy Bill will enable the Government to proceed with a domestic roll-out.’’ (Energy Retail Association, 2008). This is encouraging for demand response as the smart meters’ deployment will allow universal and accurate recording of how much and when gas or electricity is used by individuals. This will therefore allow demand response signals to be sent to customers, and the response to those signals to be accurately recorded.

There is little evidence for what the possible uptake rates of demand response tariffs in Great Britain might be. A range of trials have tested customer response to demand response tariffs in Britain (Raw and Ross, 2011; Bulkeley et al., 2014; Carmichael et al., 2014, Fell et. al., 2015). Fell et al. (2015) conducted two separate online surveys completed by a nationally representative sample of people across Great Britain; (1) 2002 people for the design survey (‘the Design Study’), and (2) 2020 people for the framing survey (‘the Framing Study’) to measure consumer demand in Great Britain for a range of demand-side response tariffs. Approximately 30% of people said that they were either strongly or moderately in favour of switching to the static time of use tariff. However, twice as many people were strongly against as were strongly in favour, and many were undecided or ambivalent. The most popular tariff by some margin was direct load control, with more than a third of people in favour of switching to it. This was also the only tariff for which more people expressed a positive, rather than a negative view towards switching. The least popular tariff was the dynamic time of use tariff without automation, which less than a quarter of people said they were in favour of switching to, and over 40% viewed negatively.

Spence et al. (2015) surveyed online a representative sample of 2,441 UK residents and found that just under 30% of people said that having their washing machine remotely triggered by a network operator to finish by a particular time would be acceptable. Half of the participants accepted the external control of fridge-freezers.

The Electricity Policy Research Group (2010) and University of Cambridge (2013) looked at potential participation in load shifting (Oseni et al., 2013; Platchkov et al., 2011) by conducting online surveys. Based on a representative sample of 1,526 UK residents, Oseni et al. (2013) measured people's stated willingness to accept demand response in a range of different electrical appliances. 30% of the participants said that they would accept pre-set operation of wet appliances (dishwashers, washing machines, tumble dryers) overnight. 50% of the participants accepted having cold appliances (refrigerators, freezers) interrupted for 1 to 3 minute intervals. They found that 32% to 36% of participants would agree to limited cooker use in return for an annual electricity bill reduction of up to £20.

These previous studies show that evidence is beginning to emerge about possible participation rates for certain demand response tariffs. However, available electricity demand flexibility does not solely depend on the size of those participating but also the influence of appliance demand shifting over the electricity power load. The remainder of this chapter will focus on examining the different appliance factors that influence household electricity demand and demand response potential.

2.3 APPLIANCE FACTORS THAT INFLUENCE HOUSEHOLD ELECTRICITY DEMAND AND DEMAND RESPONSE

Section 2.1 showed that the aggregated electricity demand from home appliances represents a significant share of household demand. As a result, household appliances are one of the key instruments to provide demand side flexibility (Strbac et al, 2010; National Action Plan for Energy Efficiency, 2010; European Commission, 2013). The cumulative effect of demand-shifting can be achieved by scheduling appliances for use at another time of the day. Therefore, the focus should be on the household appliances level, controlling and optimizing their operation (Gottwatt et al. 2011; de Blécourt 2012). To quantify the potential of demand response, a sound understanding of the types of home electric appliances and the occupant behaviour of household electrical appliance use that drives household electricity demand is needed. This is also important as these relationships are valuable in the construction of a realistic household appliance electricity demand model.

Electricity demand in homes and demand response potential depends on three main factors:

1) Ownership of home electrical appliances
2) The occupant behaviour of household electrical appliance use and power demand characteristics of these appliances
3) The suitability of appliances to be involved in a demand response scheme

The following sections present the above mentioned appliance related factors. Each type of appliance mentioned in previous studies is included in the review, indicating whether its influence on domestic electricity consumption is significant and has a potential to be part of the demand response scheme.

2.3.1 Appliance ownership

In this section, the appliance ownership in the UK is discussed. Household electrical appliances include all appliances typically found in homes such as ‘wet’ appliances (washing machines, tumble dryers, dishwashers), ‘cold’ appliances (fridges, freezers), consumer electronics (televisions, game consoles, computers), cooking appliances (hobs, cookers), electric showers and many more.

The relationship between appliance ownership (i.e. the number and types of appliances owned by households) and electricity consumption has been the subject of extensive research. Several authors acknowledge that the number of appliances have a significant influence on the household electricity demand (Tiwari, 2000; Bartiaux and Gram-Hanssen, 2005; Yohanis et al., 2008; Wiesmann et al., 2011; Bedir et al. 2013). Halvorsen & Larsen (2001) found that electricity consumption rises with the number of electrical appliances. Genjo et al. (2005) conducted a survey on the appliance ownership of 505 Japanese households. They found that lighting and appliances account for 3 MWh and 60% of the variance in annual electricity consumption in the dwellings. Carlson et al. (2013) found that 12 specific appliance types can cause up to 80% of a household’s electricity consumption. The significant effect of the ownership of desktop and laptop computers on electricity consumption has previously been acknowledged by Zhou and Teng (2013), determining that households owning a desktop computer consume approximately 10% more electricity.

Appliance ownership rates are also an important factor for the demand response potential as home appliances are one of the key instruments to provide demand flexibility. Therefore, it is important to investigate which appliances are available for shifting. For example, residential loads, which are used traditionally in demand response programs in many other countries, have a low ownership in the UK. The ownership of air-conditioning units is estimated at 2.4% (He et al., 2005) and they only operate for a short summer period, whereby electric space heater ownership is below 10% operating in short winter periods. Therefore, these appliances offer little demand response potential in the UK due to their low ownership.

Depending on the literature, there are not many significant studies of appliance ownership in the UK although some data is available from small surveys or general

market research data that has been focused on sales. Several studies focused on appliance ownership in the UK are summarized in Table 2.3.

Table 2.3 Studies conducted which present the UK appliance ownership

Name of the study	Year conducted	Number of households interviewed (sample size)	Number of types of appliances covered	Is it representative?
Mansouri et al.	1994	656	15	Slightly yes[1]
Fawcett et al.	2000	unknown	8	Unknown
40% House Project	2005	unknown	7	Unknown
Yao and Steemers	2005	unknown	14	Stated that it is based on literature review
4M Project (DECC)	2010	235	16	Unknown
Household Electricity Survey (HES 2011)	2011	251	63	No
Energy Follow-up Survey	2011	2616	21	Yes

[1]The study explains that they defined their sample as slightly representative and the sample would be more truly representative nationally if more elder recipients had responded.

A relatively small but detailed survey in the UK was first conducted by Mansouri et al. (1996). They focused on ownership levels of appliances and their utilisation patterns, as well as energy-use behaviour, energy and environmental attitudes in South-East England between May and November 1994. The analysis of the Energy Follow-Up Survey is based on the interview sample weighted to the national level, using a weighting factor specific to the interview sample and is therefore representative of the English housing stock, with a population of 21.9 million households. A selection of percentages of saturation from these studies which presented the appliance ownership in the UK is summarised in Table 2.4. For example, the percentage of saturation (saturation level) of 42 means 42% of the homes surveyed have that appliance.

Table 2.4 Saturation levels in percentages of appliance ownership in UK

		Saturation levels[1] (%) according to:[2]						
		Mansouri et al. (1996)	**Fawcett et al. (2000)**	**Yao and Steemers (2005)**	**40% House (2005)**	**4M Project (DECC 2010b)**	**Household Electricity Survey (2011)**	**Energy Follow-up Survey (2011)**
Wet appliances	Dishwasher	42	20	16	35	22	59	41
	Washing machine	93	91	88	77	87	91	97
	Tumble dryer	54	51	49	35	64	53	62
Cold appliances	Refrigerator	54	-[3]	53	43	38	50	99
	Freezers	47	42	55	-	46	48	46
	Fridge-freezers	58	60	58	60	50	74	65
Televisions		97	96	97	-	96	99	98
Cooking appliances	Microwave	74	77	74	77	-	91	80
	Electrical hob	37	-	37	-	26	4	38
	Electrical grill	-	-	-	-	18	2	70
	Electrical oven	56	53	56	-	52	20	69
	Kettles	90	-	5	95	98	99	-
Lighting		100	-	-	-	-	100	-
Electric shower		-	-	-	-	55	32	-
ICT	Desktop computers	-		-	-	50	-	-
	Laptops	-		-		51	-	-
	Video recorders	76		76		-	-	-
Iron		100	-	100	-	96c	2.4	-
Vacuum cleaner		100	-	100	-	96	82	-
Portable heaters		-	-	-	-	21	-	-

[1] The number of the houses surveyed for each study are different from each other therefore the ownership is presented in percentage.
[2] Saturation level shows the percentage of the households who have the appliance. Saturation level (%) of 42 means 42% of the homes surveyed have that appliance.
[3] "-" is put where the project does not indicate any information on that particular appliance

As can be seen from Table 2.4 ownership rates varied in the literature review. For instance, the ownership rates of dishwashers were found to be quite different. However, some appliances are in line with each other such as washing machines and kettles. Both appliances rated as the highest in UK households. The least common appliance types were electric hobs (38%). Although hobs and grills are found in the majority in UK homes, in most cases they are operated by gas rather than electricity (DECC, 2014a). Table 2.4 can be divided into sub-groups for the EFUS dataset as the appliance ownership depends on different factors. Appliance ownership and usage is related to the socio-economic characteristics of the household as well as household characteristics such as the type and age of occupants and tenure (Leahy et al. 2012). For example, Leahy and Lyons (2010) found out that income is statistically significant.

The Northern Ireland Powershift trial (Owen and Ward, 2007) suggests that low-income consumers tend to have different appliance ownership compared to average consumers, which may affect their ability to shift the demand.

2.3.2 Occupant behaviour of household electrical appliance use and power demand characteristics of these appliances

Occupant related energy usage refers to all human actions that affect the way that fuels (electricity, gas, petroleum, coal, etc.) are used to achieve desired services, including the acquisition or disposal of energy-related technologies and materials, the ways in which these are used, and the mental processes that relate to these actions (Mourik et al., 2015). Occupant behaviour in buildings can be defined as both the occupant presence and the occupant actions that may influence the building environmental conditions and the building energy consumption (Yan and Hong, 2014). Occupant behaviours include the building occupants' actions on windows, air conditioning, and heating (such as window opening, timer settings and choice of thermostat set-points) that affect hygro-thermal conditions, indoor air quality, light, noise, and temperature (Hoes et al., 2009; Guerra Santin et al, 2009; Schweiker et al., 2011) and the building occupants' use of services within the building, such as hot water, cooking and appliance usage, which consume energy and generate internal heat gains (Isaksson and Karlsson, 2006; Yamaguchi et al., 2011).

Zhou and Teng (2013) indicate that appliance ownership only partially reflects the effect of home electrical appliances on household electricity consumption. DECC (2014a) shows the ownership and electricity demand share may not always correspond. For example, although the ownership saturation of dishwasher and kettle are 40% and 99% respectively, dishwashers have more share in the annual electricity demand (2.1%) than kettles (1.2%). As many electrical appliances are controlled by occupants, the occupant behaviour usage of household electrical appliances is an important aspect for understanding electricity consumption (Swan and Ugursal, 2008; Grandjean et al., 2012). The use of electrical appliances impacts on the timing and magnitude of a household's overall electricity consumption.

Firth et al. (2007) measured the electricity consumption of 72 households in the UK over a two year monitoring period. They observed a large variation in the annual energy consumption and concluded that this probably resulted from variations in the number of occupants, the behaviour patterns of the occupants as well as the number and type of appliances used. The electricity consumption was measured at 5-minute intervals, and they observed that it significantly fluctuated according to changes in the behaviour of occupants.

Hoes et al. (2009) compared the energy demand results of the ESP-r model used in its stand alone mode with ESP-r used in combination with the Sub-Hourly Occupancy Control (SHOCC) model developed by Bourgeois (2004). They found that heating demand (9%) and cooling demand (24%) deviated significantly between these two analyses. Bedir et al. (2013) used correlation analysis and the variable “duration of use” to investigate if a correlation with electricity consumption occurred and, if so, how strong this correlation was. Afterwards, using a stepwise technique, it was placed in the regression analysis with the other correlated variables. They found that the duration of use of appliances (including ICT[3], HVAC[4], washing and laundry appliances) explained 37% of the variance in electricity consumption observed between domestic buildings.

2.3.3 Electrical appliances and demand response opportunities

As can be seen from the daily profiles of appliance electricity demand, some appliances have nearly constant demand throughout the day (such as refrigerators and freezers), whereas other appliances have higher demand in the evening (cooking devices, TVs.) or at certain times of the day (such as washing machines).

Not every appliance can be shifted or managed. Different appliances have different use patterns, runtimes, power demands, operational constraints and advantages, therefore the potential of demand response offered by the appliances will differ. A comprehensive appliance classification for demand response is needed to understand

[3] ICT stands for information and communications technology.

[4] HVAC stands for *Heating, ventilation and air conditioning* (*HVAC*)

the potential of time shifting of certain appliances, and to set up priorities and design control strategies for demand response accordingly.

Table 2.5 summarizes the categorisation of the appliances for demand response found in the literature. Yu et al. (2013) and Zhu et al. (2013) introduced a category of "power-shiftable" appliances which refers to appliances that have flexible power usages and therefore shifting of the appliance usage is not needed. In other words, these appliances possess some form of energy storage; therefore, the power consumption and the end-use service are decoupled by storage that can be in the form of (electrochemical) batteries or thermal inertia. The THINK Project (2013) considered cold appliances as power-shiftable as opposed to many other studies which considered them as non-shiftable. Cooking appliances were considered as partially-switchable meaning that it is possible to switch part of the time depending on the preferences by several studies. Several studies (Paatero and Lund 2006, THINK Project 2013) considered some of the non-shiftable appliances as responsive by interrupting/curtailing the appliance usage, indicating therefore that they can be a part of the demand response scheme.

Table 2.5 Categorization of the appliances for demand response in the literature

Appliance type	Classification	Reference study
Wet appliances	shiftable/schedulable/ switchable	Kamilaris and Pitsilledes 2011; DECC 2013a).
Cold appliances	Non-shiftable or power-shiftable	Yu et al. (2013) and Zhu et al. (2013) THINK Project (2013)
Cooking appliances	Partially-switchable	Kamilaris and Pitsilledes (2011) DECC (2013a)
Audio-visual, ICT, lighting	Non-shiftable	

A similar classification of the appliances is done in this study each implementing its own shifting logic. The classification of the appliances for different demand response actions as used in this work is presented in Table 2.6. The terms "switchable", "shiftable" and "schedulable" are frequently used interchangeably in the literature and are defined as the use that can be moved in time with a little effect on the end-use service. In this study the term "shiftable" is used. Further classifications of the shiftable appliances were made including the i) power-shiftable classification: shifting the time

of the power usage of the appliance and ii) time-shiftable: shifting the time of the usage of the appliance.

For example, a fridge can be continually used by the occupant (opening and closing the fridge whenever he/she likes) though running of compressor which is shifted without having an effect on the end-service. However, for time-shiftable appliances such as washing machines, the use of the washing machine is shifted which has a little effect on the end-service. There should be a distinct separation between the types of non-shiftable appliances as some of these appliances are permanent appliances which cannot be turned off whereby the others are on demand and spontaneous, therefore the latter can have potential for demand response by curtailing the usage.

Table 2.6 Categorisation of home appliances for demand response

Demand response action	Description	Appliances with capability for this demand response type
Power-shiftable (Time-shifting of the power usage of the appliance)	The appliances that can be used for this type of demand response possess some form of energy storage. A certain amount of electricity is required over time but the instantaneous power supply is not important therefore power usages of the appliances can be shifted without affecting the end-use service. These appliances can be fully automated.	• Electrical water heaters • Electrical space heaters • Cold appliances: Refrigerators, freezers, fridge freezers
Time-shiftable (Time-shifting of the appliance usage)	The appliances that can be used for this type of demand response are not used for momentarily urgent tasks, whereby the end-result is important to the end-user rather than the direct use of the appliance, therefore the usage of the appliance can be shifted to a future time having little effect on the end-use service as long as the task is finished before a certain time.	• Wet appliances: Washing machines, washing-drying machines, dishwashers, tumble dryers. • Irons • Vacuum cleaners • Cooking appliances: Electric ovens, hobs, grills • Electrical showers
Non-shiftable but curtaible (Curtailing the appliance usage)	These appliances have a direct use to the end-user and are operated by the user on demand at that particular moment and may not be demanded in the future time or before therefore they are not considered as shiftable with a schedule. However, the households may respond to signals instantly by curtailing the usage of appliance affecting the end use service. The presence of the occupants is needed for this demand response type as the usage is only pertinent to occupant activities.	• Lighting • Cooking appliances Kettles, microwave • ICT equipment: Laptops, desktops, printers, scanners • Audio-visual: DVD/CD players, TVs, skyboxs, HiFis • Irons • Vacuum cleaners
Non-shiftable and non-curtailable (No intervention to the usage nor the power)	These appliances have no direct-use to the user and are permanent must-run services that are always on and are never turned off. The end-use service needs instant power therefore can neither be shifted in time nor can be interrupted.	• Continuous appliances: clocks, burglar alarms, door bells, modems, routers

Demand response actions are mostly suited to power-shiftable and time-shiftable appliances as they are devices that can be shifted with little or no effect on the end-use service. These devices can fully harness the demand response. The non-shiftable appliances can contribute to the demand response by interrupting the usage of the appliance by the household with certain incentives, however, this affects the end-user. Many studies categorised some devices both as time-shiftable and on demand appliances, therefore curtailable, such as vacuum cleaners and electric ovens. This is because cooking and cleaning can be spontaneous as well as a task.

2.4 A REVIEW OF APPLIANCE ELECTRICITY DEMAND MODELLING

2.4.1 Appliance behaviour metrics for appliance usage and their definitions

There are several occupant behaviours of interest with respect to appliance usage modelling. A review of the literature has identified a number of occupant behaviours for household appliance usage including the time of day when occupants switch-on the appliances, the frequency of appliance use, the length of time for which the appliance is switched on, the choice of power mode or cycle programme, and the potential for interaction between the use of difference appliance types (for example a tumble dryer may be switched on following the use of a washing machine). It is complex to categorise occupant behaviour metrics for appliances. For example, switching on a television (TV) is solely due to occupant behaviour whereas switch-on times of a fridge is dependent on the fridge compressor but it is also affected by actions such as door opening or storing new food which is performed by the occupant.

Table 2.7 summarises the five main occupant and appliance behaviour metrics identified in literature. These metrics are 1) number of switch-on events, the count of switch-on events which occur over a specified time period; 2) switch-on time of day, the times when the switch-on events occur; 3) duration, the length of time for which the appliance is used; 4) choice of programme/power demand levels and 5) behaviour towards stand-by mode.

In the literature, a switch-on event is defined as the beginning of use of an appliance. Switch-on events for cold appliances are defined as the switch-on of the compressor. Durations are defined as the periods between the switch-on and either switch-off or stand-by event of appliance use. Stand-by use occurs when an appliance is not in use but is still consuming power (Cogan et al., 2006). Consumer electronic equipment such as televisions and set-top boxes have stand-by modes where the occupant can leave appliances on stand-by or switch them completely off (Firth et al., 2008). Page (2007) defines the behaviour towards the stand-by power as whether or not the occupant leaves the appliance in this stand-by mode when not using it. For wet appliances occupants are actively involved in loading and starting the appliance (the switch-on times) but do not directly choose the duration or switch-off times. Although there is no interaction with the user while running, as the power demand and duration of the cycle are highly dependent on the washing temperature and the amount of water needed, occupant behaviour is a significant factor through the choice of the washing machine programme. Televisions, cooking appliances and showers are actively switched on or off by the occupants. The duration of these appliances is directly related to the activities of the occupants. Cold appliances are in use continuously and the user has no direct interaction with the switch-on or switch-off times however the duration is affected by occupant’s door opening or storing food inside.

Table 2.7 Review of occupant and appliance behaviour metrics in literature

Appliance behaviour metric	As applies to:	Definitions made by previous studies in literature.
Number of switch-on events	- Wet appliances, TVs, cooking appliances, electric showers	- Paatero and Lund (2006) defines a constant mean daily number of switch-on events for each appliance however, does not use it as an explanatory variable but to calculate the starting probability function (P_{start}) (Paatero and Lund, 2006).
	- Cold appliances	- Widén and Wäckelgård (2010) defines the number of cycles of cold appliances constant during each day.
Switch-on time of day	- Wet appliances, cooking appliances, TVs, electric showers	- Switch-on time of an appliance is defined based on time of the day (Capasso et al. 1994; Paatero and Lund 2006; Page 2007; Wilké et al. 2013). These studies develop switch-on times probabilities from the ratio of times the activity was started over the total number of times. It shows the likelihood of a state change (e.g occupant switches-on the TV). - Widén et al. (2011) does not define the switch-on time based on a time of the day but depending on a transition probability for switching between states i and j. (e.g. switching-on a tumbler dryer after washing machine).
	- Cold appliances	- Cold appliances are modelled as fixed profiles therefore switch-on time of the day is not defined. (Capasso et al. 1994; Paatero and Lund 2006; Page 2007; Wilké et al. 2013).
Duration	- Wet appliances, cooking appliances, TVs, electric showers, cold appliances	- Majority of the studies define the duration of the appliance use as the period between the switch-on and switch-off moments. - Page (2007) and Wilké et al. (2013) computed the duration of appliance usage from the distributions derived from the monitored dataset. - Richardson et al (2011) and Widén et al. (2011) do not modelled the duration of the appliance use explicitly. They used Markov chain models in which only transitions between activities are modelled - Paatero and Lund (2006) used fixed durations taken from manufactures for each appliance use.
Choice of Programme	- Wet appliances - Cooking appliances, TVs, electric showers	- Each activity is connected to a certain appliance with fixed and predefined load cycles for different types of appliances. (Paatero and Lund 2006; Page 2007; Widén et al. 2011; Yamaguchi et al. 2011)
	- Cold appliances	- Fixed power demand is used for cold appliance (Paatero and Lund, 2006; Page, 2007; Widén et al., 2011).
Behaviour towards stand-by power	- TVs	- Page (2007) derived stand-by powers from the measurements. Behaviour of stand-by is defined with probability functions which is the ratio of leaving the appliance on stand-by to switching-off and leaving the appliance on stand-by.

2.4.2 Previous household appliance electricity demand models

This section presents an up-to-date review of the various modelling techniques used for residential sector electricity demand and demand response.

Over the last few decades, a variety of methods have been developed to model residential sector energy consumption and residential power demand. The development of models is a cost-effective option as it allows reduction of demand investigations particularly in cases where technological advances and behavioural changes in residential electricity demand are considered. Grandjean et al. (2012) and Swan and Ugursal (2009) have published a very thorough review on residential electric load curve models and modelling techniques. Grandjean et al. (2012) presented a review of published residential electric load curve models and classified models into the four types which are i) deterministic statistical disaggregation, ii) statistical random models, iii) probabilistic empirical models and iv) time-of-use models. Swan and Ugursal (2009) have published a very thorough review on residential electric load curve models and modelling techniques. They identified two distinctive approaches which are top-down and bottom-up models and further divided the bottom up approach to deterministic and stochastic models. Stochastic models were categorised agent based models, statistical random models, empirical models and time of use based models. Fischer et al. (2015) divided models of the residential electricity demand into two groups: statistical models and bottom-up models. Statistical models are basically data-driven in which the behaviour of electricity demand observed in the measured data is reproduced by using statistical techniques. In the bottom-up approach, the total electricity demand is modelled as sum of the consumption of individual appliances. Each technique has different levels of input information, simulation techniques and refers to different applications. In the literature, two distinctive approaches are identified: top-down and bottom-up models. Categories of top-down and bottom-up techniques for modelling residential energy consumption are shown in Figure 2.5.

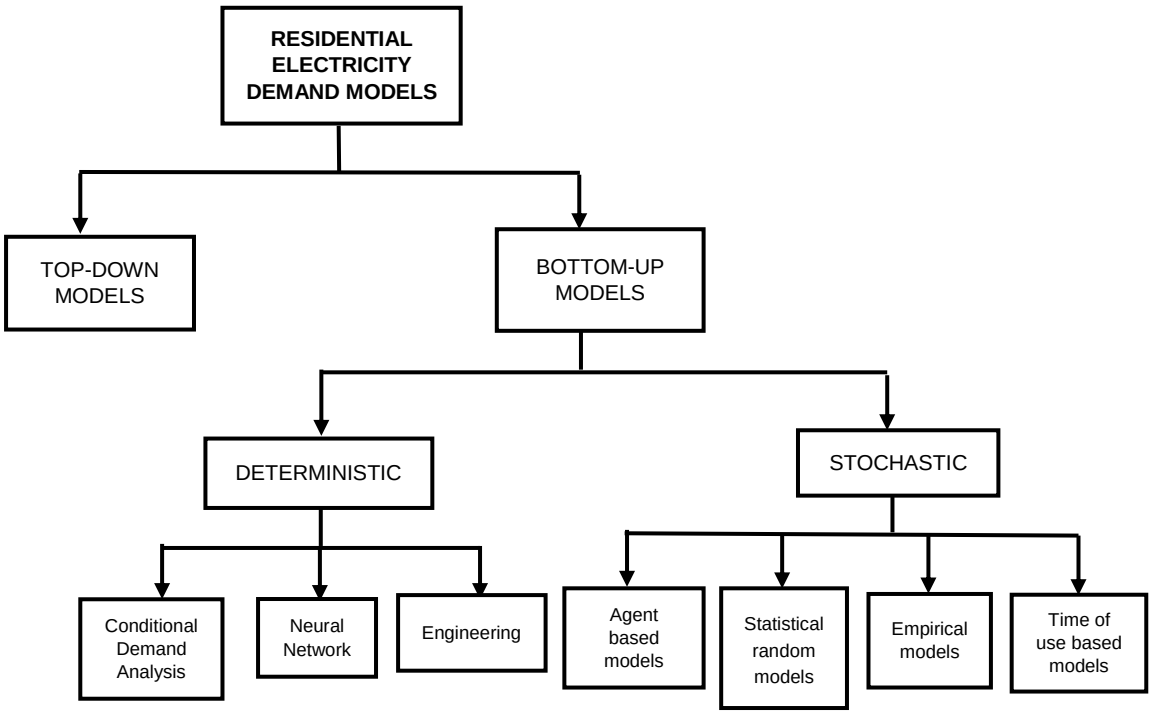


Figure 2.5 Top-down and bottom-up models for residential electricity demand

The top-down models treat the residential sector as an energy sink. The models use estimates of the total residential sector energy consumption to attribute energy consumption characteristics of the residential sector (Muratori et al., 2013). They usually regress or apply factors that affect consumption to determine trends and are not concerned with individual end-use (Baltagi, 2002; Swan and Ugursal, 2009). Due to a lack of detail in individual end-use consumption, they have a limited capability to assess the impact of demand shifting of appliances in individual buildings. Therefore, the requirements of this study cannot be met by top-down modelling.

Bottom-up models identify the contribution of each end-use to the aggregate energy consumption (Capasso et al., 1994; Richardson et al., 2008; Widén et al., 2010). These models calculate the energy consumption of an individual or group of households including the data of individual consumption of appliances, their technical characteristics and the occupants' behaviours. Moreover, a bottom-up modelling approach allows the user to modify and extend the simulations using the components of the model to evaluate the impact of different appliances, future technologies and different usage patterns as high level of detail (Capasso et al., 1994; Richardson et

al., 2010; Widén et al., 2011). Therefore, a bottom-up approach is chosen for this study.

Bottom-up models can be divided into several subgroups regarding the methods they use. Swan and Ugursal (2009) have classified them into two groups which are statistical and engineering methods. In another review published by Grandjean et al. (2012), the models were classified according to the scale of complexity level of diversity of the models. In this study, the bottom-up models are classified as deterministic and stochastic approaches.

In the deterministic models diversity is not modelled, as it is embedded in the measured data in a deterministic way (Grandjean et al., 2012). Therefore, with the deterministic approach, the output of the model will have the same limitations as the original set. Conditional Demand Analysis and Neural Networks are highly regarded statistical models that represent the two commonly used energy modelling techniques to allocate total household energy consumption among the various end-uses and determine the attractive targets for both consumption reduction and load shifting programmes and policies (Parti et Parti, 1980; Aigner et al., 1984; Aydinalp et al., 2003; Yang et al., 2005). However, they are not flexible with regard to modelling new technologies as they need historical consumption data. As a result, they have limited capability to assess the impact of demand response. Engineering methods with deterministic approaches explicitly account for the energy consumption of end-use based on power ratings and the use of equipment based on thermodynamic principles. However, occupants interacting with appliances in building simulation tools are currently represented in terms of fixed static schedules (Hoes et al., 2009). Simulation tools such as DOE-2, BLAST and EnergyPlus typically use one average profile corresponding to the use of different types of appliances based on a library of typical profiles such as residential or office work. The values of the profile are multiplied by the installed power of each appliance type (Abushakra and Claridge, 2001). For deterministic approaches they may find that all peaks occur at the same time, however in reality, this may not be the case as not all peaks may not occur at the same time due variation in occupant behaviour. Tanimoto and Hagishima (2010) found that such procedures can lead to unrealistic and overestimated peak values as defining standard behaviour for types of households fails to consider the random variability of the occupant behaviour. Secondly, Baetens and Saelens (2011) indicate that increased

quantity and higher value voltage drops in electricity demand are noticed due to randomness, and the use of deterministic profiles may strongly underestimate this, therefore underestimating the problem of grid instability. Hence, assuming a ‘standard dwelling’ and a ‘standard schedule’ seems inappropriate as it fails to consider the random variability of the demand. Thirdly, field measurements may suffer limitation to only a few datasets (Fischer et al. 2015). The combination of a few available measured load profiles can lead to statistically irrelevant outcomes as it is not consisting of different household types such as multifamily houses etc. Aggregation of a limited number of load profiles will lead to a summation of peaks while neglecting smoothing effects.

The use of a stochastic model for the generation of load profiles can overcome these drawbacks, since each output load profile will most certainly be different from the ones already generated. Researchers have developed a number of stochastic occupant behaviour and appliance usage models in order to include the randomness linked to the differences in occupant behaviour between households and the variation in time of each behaviour. Stochastic models typically use a set of probability density functions. In a stochastic process, there is some indeterminacy in its future evolution described by these probability distributions. This means that there are many possibilities the process might go to, but some paths are more probable and others less. Probability functions such as availability and tendency to use represent the likelihood of the different appliances being used at different times of the day to generate a diversity of results and were firstly developed by Walker and Pokoski (1985). A pioneering bottom-up and stochastic model was developed by Capasso et al. (1994), where the availability and appliance usage starts are represented by probabilistic functions which are used together with household characteristics and electricity demand for appliance cycles to predict the residential electricity demand profiles. Table 2.9 summarises several stochastic models developed for appliance use in the literature with modelling techniques and datasets they used.

Table 2.8 Bottom-up household appliance electricity demand models with stochastic approach

Agent-based models

- The heart of the model is the objective function which is defined by the set of possible states of the network, representing the 'rules for network behaviour' of the agents and determining how likely it is for the agent to change its network in a particular way.

Example studies:

- De Blécourt (2012) tested the effectiveness of different scheduling schemes on a low-voltage network with households that own non-smart and smart appliances using a multi-agent modelling programme Netlogo.

Statistical data models

- Probability functions are assigned to appliances relying on the public statistical data related to the monitored electricity demand of appliances.

Example studies:

- Yao and Steemers (2005) present a simple method to predict electricity demand profiles on pre-defined occupancy and appliance consumption patterns.
- Paatero and Lund (2006) presented simple demand side management cases applying to the 10,000 household load data generated by the 1-hour resolution domestic model. Apart from the time of the day, the model depends on a seasonal and a social random factor as well as the week day.
- Armstrong et al. (2009) present a stochastic model using the average national data about residential electricity use for appliances and lighting to predict the electricity load profiles of Canadian households.
- Gottwalt et al. (2011) developed an algorithm that simulates residential load shifting under real-time-pricing using the generated electricity demand based on the resident probability functions of availability. They generated household electricity load profiles using electricity consumption data from Germany.
- Dickert and Schegner (2011) model load curves of individual residential appliances as a function of switch-on times, duration distributions and power consumption distributions that are normally distributed around their mean value.

Time of use based models

- Occupancy patterns are used as the key driver in determining the residential energy use.
- Appliance usage is mapped according to the occupancy model based on the detailed sequences of daily activities in households collected through diaries.

Example studies:

- Richardson et al. (2006) developed a 1-minute resolution domestic electricity model using the 10,000 households Time-of Use survey. In simulation, households were populated with same appliances, and activity sequences is stochastically modelled with first-order discrete-time Markov-chains[5] and the activities are converted into electricity demand profiles using a calibration factor.
- Tabak and de Vries (2010) used a random probability function to determine the start time of 9 specific activities in an office written by 8 people however they did not generate electricity demand.
- Widén et al. (2009, 2011, 2012) developed a stochastic model to predict appliance use patterns based on first-order Markov chains. They developed power conversion functions that were pre-defined to convert the activities to power demand of appliances. Similar approach was taken by the studies of Widén and Wäckelgård (2010) and Muratori et al. (2013).
- Wilke et al. (2013) proposed a bottom-up approach which allows residential activities to be modelled as a function of time and individual specificities. the activity of household members is independently simulated by repeating the following two processes: the selection of an activity starting using the time-dependent probability of start of activities via Monte Carlo simulation and the selection of the duration of the selected activity. They used a time use data based on one day diaries of 15441 individuals (7949 households).
- Tanimoto et al. (2007, 2008, 2011, 2012) stochastically generated time-dependent occupant behaviour schedules for heating and air-conditioning systems with Markov chains based on their survey on time use of 12,600 Japanese residents

Empirical data

- Probability functions are assigned to appliances relying on the monitored data using electrical power sensors of appliances for extended periods.

Example studies

- Page (2007) developed an appliance use model using start time probabilities and distribution of durations using the monitored household appliances. The model is based on the monitored data of 8 persons working in academia for 38 weeks and 8 different residential buildings for 2 weeks.

[5] More information on the formulas and modelling theory of Markov chain is available at: Cinlar, E., 1975. Introduction to stochastic processes. Prentice-Hall.

2.4.3 Limitations of the existing models

Characterising the stochastic nature of occupant behaviour has proved to be non-trivial and previous researchers have identified several constraints to progress including the lack of a common modelling approach, the lack of a rigorous model validation framework, the lack of experimental designs and the lack of suitable monitoring data with which to develop models (Yan and Hong, 2014; Yan et al., 2015).

Wilké et al. (2013) shows that models based on first-order Markov chains as described in Yamaguchi et al. (2011) and Richardson et al. (2010) are not able to model the duration distributions coherently. The reason for this is that the transition probabilities used in first-order Markov chains do not depend on the time of the activity/appliance use when started.

Furthermore, most of the models (Widén et al., 2009, 2011, 2012; Page, 2007) were not validated fully by comparing the distribution of predicted electricity demand profiles with the measured values. The models of Armstrong et al. (2009) were widely used by many researchers however Saldanha and Beausoleil-Morrison (2012) revealed that their model does not adequately reproduce neither the inter-household variations demand nor the temporal variability of the electricity demand profiles.

These studies used time of use (TOU) data to obtain appliance usage probability, which is converted to an appliance pattern. Models based on time of use data obtain appliance usage probability from the activities written, which is converted to an appliance pattern. Sometimes this is problematic, since the conversion is not rigorously defined. For instance; as occupants note down activities for each 10 or 15-minute period within the day, the switch-on times cannot be identified precisely. Moreover, cross-correlations between appliances are not captured because of the conversion (someone can switch-on the TV while he/she is cooking). Another limitation is the use of one-day diary based time of use datasets which fail to capture the difference in behaviour for an extended period of time and the difference in durations and choice of programme between usages.

Torriti (2014) raised the lack of the intra-variation (household variation is the difference in occupant behaviour within the household) as an important issue in the residential energy demand models using time use data. For example, time use data are representative for average days, typically weekdays, where societal constraints standardise routine and practice of everyday life. However, most sizeable peak events take places on non-average days due to either weather conditions (too cold/hot days; or rare public events), and these variations among different days of the same household are not considered. The models which use time use data suffer from this issue as time use data is usually collected from a large number of people and a limited number of days.

Other studies analysed the measured sensor data to obtain the switch-on times, duration and the power demand profiles (Page, 2007). The limitation of these studies is that as monitoring is expensive, long-term studies in literature only contain information relating to a small sample size (2 to 10 homes) thus cannot be considered representative for a large aggregate and able to capture behavioural diversity among different groups.

2.4.4 A Review of Demand Response Modelling

There are several studies focused on demand response modelling. Paatero and Lund (2006) demonstrated demand side management cases on an individual appliance level using the bottom-up stochastic model that they have developed. However, they did not perform the demand response stochastically. Instead, they either shifted the cold appliances and wet appliances to a later time or cut the usage of the cooking appliances or audio-visual appliances deterministically.

Esser et al. (2006) used a two-step model. First the load curve of a household under a flat electricity tariff is stochastically generated, then the household's resulting electricity consumption is optimized taking price differences for different times of the day.

Widén et al. (2012) developed a bottom-up stochastic model where demand response to time-differentiated tariffs were defined. The response to the price signals was then modelled by up-shifting the probabilities for switching to electricity-dependent activities

during low-load pricing while down-shifting the probabilities for switching to other activities, and vice versa during high-load periods.

Gottwalt et al. (2011) presented a stochastic bottom-up model that generates household load profiles under flat tariffs and simulates changes in these profiles when households are equipped with smart appliances, such as cold appliances and wet appliances in their study, and when households are given time-based electricity prices. Depending on the price at a particular time, the households may then either start the dishwasher directly or select a cheaper slot. Probabilities for shifting the appliances to a cheap slot are assumed by the researchers as there is no reliable empirical data available.

To assess the potential of this load-shifting, de Blécourt (2012) constructed an agent-based simulation model of a low-voltage network with households that own non-schedulable and schedulable appliances. The effectiveness of smart scheduling on reducing the peak loads in the network by shifting loads from peak periods to off-peak periods was tested using different scheduling schemes.

2.5 CHAPTER 2: SUMMARY

This chapter has provided an overview of the UK residential electricity consumption and the definitions of demand flexibility and demand response. It has also provided a literature review of occupant behaviour and appliance factors that influence domestic electricity consumption. Several studies have acknowledged and quantified the effect of the appliance ownership and occupant behaviour on the household electricity demand profiles.

This literature review has also identified previous studies which developed appliance use models to predict household electricity demand profiles. This review has shown the lack of a common modelling approach, as well as the lack of experimental designs and suitable monitoring data from which to develop models. This deficit in knowledge could restrict both the effective policies for demand side management and plans for future energy systems.

Importantly, this review has revealed a lack of datasets specifically focusing on the variability of appliance usage within households. The studies were restricted to up to 10 households which mainly consisted of colleagues or the working habitat. This review underlines the need for a validated model which enables prediction of household appliance electricity demand profiles. This validation should be done on a metric level as well as an appliance level in order to test the mathematical formulas behind the model. This way the methodology is assessed thoroughly on which metric the model is successful or not.

3 METHODS

3.1 INTRODUCTION

This chapter describes the methods used in developing the stochastic bottom-up household appliance usage model (HAU) and the application of the HAU model for investigating the demand response potential in the UK residential sector. The steps in constructing the HAU model can be presented as i) data collection and processing, ii) identifying which appliance types to model, iii) developing the stochastic appliance behaviour model, iv) converting the appliance behaviour events to power demand profiles, v) validating the model, vi) assigning appliance ownership to the homes, and vi) assigning power demand profiles for the sample households allocated with appliances. Finally, a study is presented to show how demand response can be modelled using the HAU model. The model development methods derive information from the existing national surveys of household appliances usage and use statistical analysis and stochastic modelling techniques to construct the household appliance electricity demand profiles. The final model is compared with the national statistics and then used to explore the demand response potential of the household appliances.

Section 3.3 describes the data collection and data cleaning process of the three datasets used in the HAU model. The three datasets are the 2013-2014 English Housing Survey (EHS), the 2011 Energy Follow-up Use Survey (EFUS) and the 2011 UK Government's 'Household Electricity Survey' (HES). The EHS is a general survey of English housing and it is nationally representative, the EFUS is the most up to date and detailed survey of appliance ownership and the HES is one of the most comprehensive datasets of household appliance usage.

Section 3.4 establishes the selected group of appliances that will be modelled in this study. This is based on a literature review of appliances that are most frequently found in households, their contribution to the electricity load profiles and capability of being part of a demand response study.

Section 3.5 identifies the occupant and appliance behaviour metrics to describe the behaviour of electrical appliance use. These include: i) the number of switch-on events that occur over a specified time period (e.g. a day or a month); ii) the time of day when the switch-on events occur; and iii) the duration of appliance use (the length of time that the appliance is switched on for). This section outlines the method of bottom-up stochastic modelling of the HAU model and appliance ownership modelling.

Section 3.6 describes the method of validation used for the HAU model. Firstly, internal validation is done on the whole dataset through comparison analysis of appliance behaviour metrics and daily appliance power demand profiles. Secondly, the national statistics are presented for the comparison of the HAU model.

Section 3.7 explains the application of the HAU model where demand shifting of the appliances is stochastically modelled to evaluate the extent that electricity demand could be shaped by time shifting. The methods for modelling a demand response case for an aggregate household electricity demand profile are explained.

3.2 OVERVIEW OF THE HOUSEHOLD APPLIANCE USAGE MODEL

Figure 3.1 presents a simple overview of the development of the HAU model. Each of the sub-models has different function and the three datasets are used for different sub-models. It consists of three parts. Firstly, a national representative household sample is chosen to provide a platform to generate the electricity demand profiles. Secondly, an appliance ownership model is developed where the nationally representative household sample is populated with electrical appliances. Thirdly, the occupant behaviour model is developed where occupant behaviour metrics are simulated using monitored data and electricity demand profiles are generated using the results of the appliance behaviour model. Following this, the aggregated electricity demand profiles are simulated by using the occupant behaviour model and converting the occupant behaviour model results to power demand profiles, where every appliance in each household is modelled individually depending on the appliance type and household type that exists in the sample.

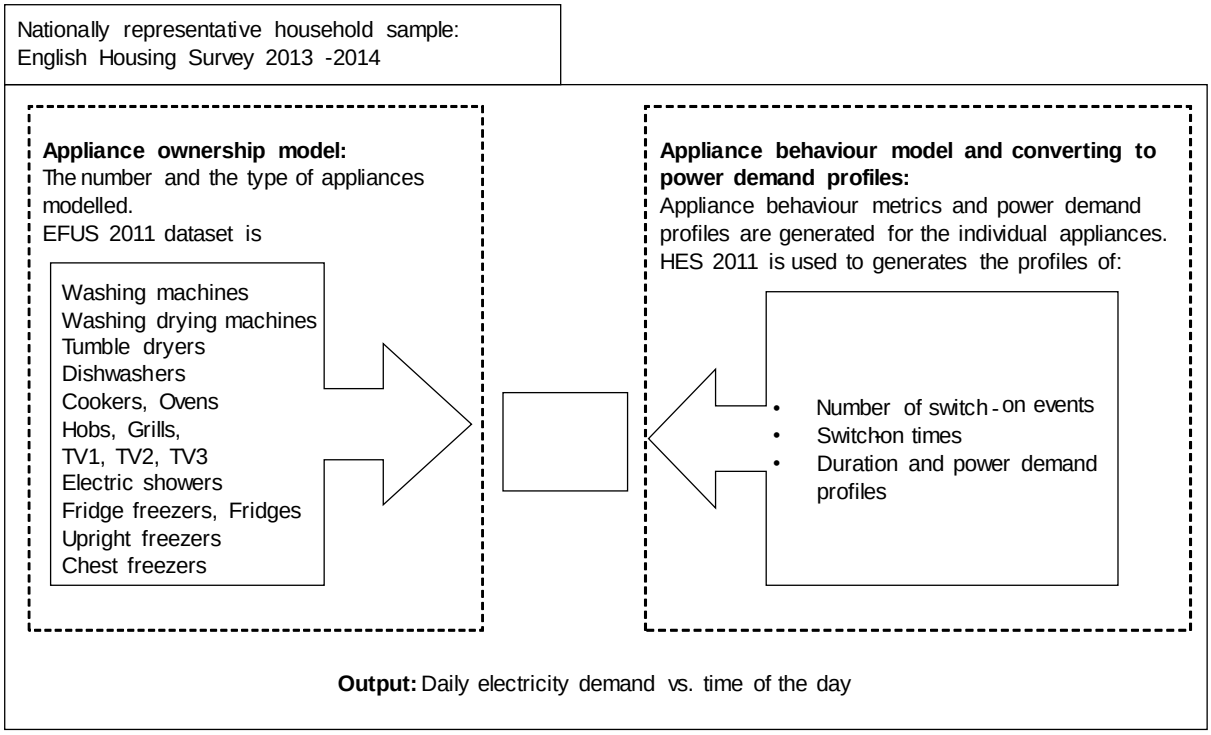


Figure 3.1 Overview of the development of the HAU model

For the first part of the model, a nationally representative sample of households is needed to provide a platform to generate the electricity demand profiles. The requirements for choosing this sample are:

- Detailed information at the individual household level
- A large sample to enable statistical evaluation
- A nationally representative sample
- Data about the household and building characteristics that could be important for modelling appliance ownership and appliance usage

The 2013-2014 EHS dataset meets the requirements mentioned above as the survey provides reliable, nationally representative and the most up to date data on the state of housing and household characteristics in England. In the EHS survey, addresses were selected using a systematic random sample design which delivers a representative sample of households in England. More details on the 2013-2014 EHS is given in Section 3.3.1.

For the second part of the model, the appliance ownership model, the number and the type of appliances are required for each household in the sample in order to generate the appliance electricity demand profiles for individual households. To achieve this, nationally representative appliance ownership will be modelled using national appliance ownership statistics. The requirements for choosing a sample to model the appliance ownership model are:

- Appliance ownership: appliance types and number of appliances in the homes collected at the individual household level
- A large sample to enable statistical evaluation
- A nationally representative sample
- Household composition similar to the EHS dataset as the appliance ownership depends on the household characteristics.

Based on the literature review (Table 2.3), it is clear that the 2011 EFUS dataset meets the requirements mentioned above. The EFUS dataset provides reliable, nationally representative, detailed and the most up to date information on appliance ownership regarding household composition compared to other studies in the UK. More details on the 2011 EFUS is given in Section 3.3.2.

For the third part of the model, the appliance behaviour model, information including individual appliance usage patterns, how and when occupants use appliances, is required to develop a bottom-up HAU model for individual households. The requirements for choosing a sample to infer this information and to model the HAU model are:

- Detailed information on individual appliance usages for a bottom-up model
- A high resolution dataset
- Very detailed appliance usage: identifying switch-on times, frequency and duration of use of appliances, power demand profiles of individual appliances, and stand-by power.
- A large sample to enable statistical evaluation
- A nationally representative sample

- A household composition similar to the EHS dataset, as the appliance ownership depends on the household characteristics.

The 2011 HES dataset meets the requirements mentioned where the electric power demands of 251 households and approximately 5,860 individual electrical appliances have been monitored during a month or a year. The monitored data provides reliable, the most up to date and high resolution of monitoring of individual electrical appliances in the UK. Monitoring the household for a period (1 month or 1 year) enables investigation of different appliance usage habits. However, a criticism of this dataset is that it has not been judged as being nationally representative of UK households. More details on the 2011 HES is given in Section 3.3.3.

Several computer programming languages and software tools are used for data analysis and development of the stochastic HAU model. Microsoft Access 2013 and Matlab are used to identify the occupant metrics, analyse the dataset for appliance ownership from the 2011 EFUS dataset and analyse the characteristics of the appliance usage in the HES dataset. SPSS is used to perform a one-way Analysis of Variance (ANOVA) test, to test the effect of household characteristics on occupant behaviour metrics. The whole model (household types, appliance ownership and electricity demand profiles) and the probability functions have been implemented as a Matlab script. The stochastic process is also implemented in Matlab by using the random number generator.

3.3 DATASETS

This section gives more detailed information about the three datasets used to develop the HAU model. Table 3.1 summarises the information derived from these datasets for different model functions and the number of households surveyed or monitored.

Table 3.1 Datasets used for developing the Household Appliance Usage (HAU) model

Dataset	Information derived	Number of homes surveyed
2013-2014 English Housing Survey (EHS)	Household characteristic are derived to have a nationally representative household sample for developing household appliance usage model.	13,276
2011 EFUS (Energy Follow-up Survey)	Appliance saturation levels are used to model the appliance ownership to be used for the household appliance usage model	2,616
2011 HES (Household Electricity Survey)	Appliance usage patterns and appliance operating characteristics are derived from the dataset to develop the appliance behaviour modelling and converting these to electricity demand profiles for the HAU model	251

3.3.1 2013-1014 EHS (English Household Survey)

The EHS is a national survey commissioned by the Department for Communities and Local Government (DCLG) that collects information about people's housing circumstances and the condition and energy efficiency of housing in England. It is stated in its current form, it was first run in 2008-2009. Prior to then, the survey was run as two stand-alone surveys: the English House Condition Survey and the Survey of English Housing. This research only uses the findings from the 2013-14 survey. The survey has a complex multi-stage methodology consisting of two main elements: an initial interview survey of 13,276 households with a follow up physical inspection of a sub-sample of approximately 6,200 of these dwellings, including vacant dwellings. There are five reports which are published following each survey year. The list of publications of 2013-2014 EHS survey is presented in Table 3.2.

Table 3.2 List of publications of 2013-2014 EHS survey

Report name	Description
EHS Headline Report	The report presents preliminary headline findings including key indicators related to departmental housing policies in areas such as trends in tenure and household composition, overcrowding, housing costs, and the condition and energy performance of the stock.
Households Report	Based mainly on the full interview sample and presents comprehensive analysis of housing trends across each of the sectors and for different household groups including changing tenure patterns, overcrowding and under-occupation, rents and mortgages.
Profile of English Housing	Presents the findings on type and age of dwellings, profile of new builds, amenities and services, accessibility and dwelling condition.
Energy Efficiency of English Housing	Presents the finding on insulation, heating, SAP rating, carbon dioxide emissions, hard-to-treat homes and renewable energy.
Fire and Fire Safety	Presents the findings on smoke alarms and other fire safety measures and fire hazards.

The links to the EHS dataset were downloaded from the UK Data Service in SPSS format. The interviews from each household were compiled into a database. The EHS dataset contains 926 variables per home on income, household characteristics, tenure, energy use, identity, second homes etc. A screenshot of the examples of variables that are related to household characteristic is presented in Figure 3.2.

Household ID	Household composition 1	House type	Age band of youngest person	Income	Bought with mortgage/loan(s)	Country of birth
1	lone parent with dependent child(ren)	Detached	0-15	£500 but less than £600 a week	yes	England
2	one female	Semi-detached	25 - 59	£500 but less than £600 a week	no	Scotland
3	couple with dependent child(ren)	Detached	0-15	£200 but less than £300 a week	no	Scotland
4	couple with dependent child(ren)	Terrace	0-15	Over £1000 a week	no	Elsewhere outside of UK
5	one female	Detached	25 - 59	£500 but less than £600 a week	yes	England
6	other multi-person households	Semi-detached	60 - 74	£700 but less than £800 a week	yes	England
7	other multi-person households	Semi-detached	25 - 59	Over £1000 a week	yes	England
8	one female	Terrace	25 - 59	£500 but less than £600 a week	yes	Scotland
9	lone parent with dependent child(ren)	Detached	0-15	Over £1000 a week	yes	Elsewhere outside of UK
10	lone parent with dependent child(ren)	Semi-detached	0-15	£200 but less than £300 a week	no	Wales
11	couple, no dependent child(ren)	does not apply	60 - 74	£500 but less than £600 a week	no	Elsewhere outside of UK
12	one female	Terrace	60 - 74	£700 but less than £800 a week	no	England
13	couple, no dependent child(ren)	Detached	25 - 59	£600 but less than £700 a week	yes	Elsewhere outside of UK
14	one female	Detached	25 - 59	£500 but less than £600 a week	no	England
15	couple with dependent child(ren)	does not apply	25 - 59	Over £1000 a week	no	England
16	other multi-person households	Semi-detached	60 - 74	£600 but less than £700 a week	yes	Elsewhere outside of UK
17	other multi-person households	Detached	25 - 59	£700 but less than £800 a week	no	Elsewhere outside of UK
18	other multi-person households	Semi-detached	25 - 59	£500 but less than £600 a week	yes	England
19	couple with dependent child(ren)	Detached	15-24	£600 but less than £700 a week	no	England
20	couple with dependent child(ren)	Detached	0-15	£500 but less than £600 a week	no	England

Figure 3.2 A screenshot of the 2013-2014 EHS household data which forms the "household sample" for the national bottom-up Household Appliance Usage (HAU) model.

A weighting factor is included in the dataset and can be applied when scaling the results to obtain unbiased national estimates that reflect the entire English housing stock. The weighting methodology involves a series of steps, each of which is designed to take into account the selection and response processes involved (Department for Communities and Local Government, 2014).

3.3.2 2011 Energy Follow-up Survey (EFUS)

The 2011 Energy Follow-Up Survey (EFUS) is one of the most recent appliance ownership surveys with a representative sample. The EFUS is a follow up survey of a subset of households as part of the EHS and has collected ownership for key appliances across England through interviews with 2,616 households. The project was sponsored by the Department of Energy and Climate Change (now Department for Business, Energy & Industrial Strategy) and the data were collected by GfK NOP. 2,616 households were interviewed face-to-face and an additional sub-sample of these households was selected to have temperature loggers and electricity monitors installed.

The links to the 2011 EFUS dataset were downloaded from the UK Data Service in SPSS format. The interviews from each household were compiled into a database. The 2011 EFUS has collected 1,309 variables per home including appliance ownership, cooking and appliance usage, heating, dwelling improvements, hot water usage, overheating, lighting, tariffs, conservatory usage and many more. A screenshot of an example of the variables that are related to the appliance ownership model is presented in Figure 3.3:

Household	Do you have a Automatic washing machine?	How old is your fridge-freezer?	In a typical summer, how many times do you use the tumble dryer?	How many TVs do you have in the home?	Does your oven use - Oil?
1	yes	At least 1 but less than 2 years old	1	1	no
2	yes	10 years old or more	2	2	no
3	yes	10 years old or more	4	2	no
4	yes	At least 1 but less than 2 years old	2	3	no
5	yes	At least 4 but less than 6 years old	3	1	no
6	yes	At least 6 but less than 8 years old	2	1	no
7	yes	At least 1 but less than 2 years old	2	1	yes
8	no	At least 4 but less than 6 years old	4	2	yes
9	no	10 years old or more	5	2	no
10	yes	At least 1 but less than 2 years old	1	2	no
11	yes	At least 6 but less than 8 years old	1	3	no
12	yes	At least 1 but less than 2 years old	3	2	no
13	yes	At least 1 but less than 2 years old	3	2	no
14	yes	At least 6 but less than 8 years old	2	1	no
15	yes	At least 4 but less than 6 years old	1	2	no
16	yes	At least 4 but less than 6 years old	5	1	no
17	yes	10 years old or more	2	2	no
18	yes	At least 4 but less than 6 years old	1	2	no
19	yes	At least 6 but less than 8 years old	2	1	no
20	yes	At least 1 but less than 2 years old	1	1	yes

Figure 3.3 A screenshot of the 2011 EFUS data which is used for modelling the appliance ownership for the Household Appliance Usage (HAU) model.

Analysis on the appliance ownership is based on the interview sample scaled up to the national level, using a weighting factor specific to the interview sample (2,616 households). Therefore, the results presented in the EFUS reports are representative of the English housing stock, with a population of 21.9 million households. A weighting process was used for the appliance ownership interview survey where data was weighted back to the population targets for tenure, Government Office Region and dwelling type.

The list of properties and characteristics collected about the appliances in the 2011 EFUS dataset, and cookers and electric showers in the 2011 HES dataset, are presented in Table 3.3.

Table 3.3 List of appliances and their characteristics that were collected in the 2011 EFUS and HES datasets

Appliance Category	Appliances covered in the EFUS dataset	The number of appliances	Age of the appliance	Size of the appliance	Label	Brand	Source of data collected
Wet appliances	Washing machines	yes*	yes	no	no	no	2011 EFUS
	Tumble dryers	yes	yes	no	no	no	2011 EFUS
	Washing-drying machines	yes	yes	no	no	no	2011 EFUS
	Dishwashers	yes	yes	no	no	no	2011 EFUS
Cooking Appliances	Cooker	yes	no	no	no	no	2011 HES
	Hob	yes	no	no	no	no	2011 EFUS
	Grill	yes	no	no	no	no	2011 EFUS
	Oven	yes	yes	no	no	no	2011 EFUS
Televisions		yes	yes	yes	yes	yes	2011 HES
Electric shower		yes	yes	no	yes	yes	2011 HES
Cold appliances	Separate fridge with ice-box	yes	yes	no	no	no	2011 EFUS
	Separate fridge without ice-box	yes	yes	no	no	no	2011 EFUS
	Fridge freezer	yes	yes	no	no	no	2011 EFUS
	Separate freezer	yes	yes	no	no	no	2011 EFUS

*"yes" indicates the information exists in the dataset whereas "no" indicates there is no information in the dataset.

The list of publications using the EFUS dataset is presented in Table 3.4.

Table 3.4 List of publications using the EFUS dataset

Publication name	Description
Summary of findings (Report 1)	Briefly summarises the key findings from the primary analysis of the survey data.
Mean household temperatures (Report 2)	Presents the headline results from an analysis of the mean room temperatures derived from the 2011 Energy Follow-Up Survey (EFUS).
Metered fuel consumption (Report 3)	Presents the results from an analysis of the median gas and electricity consumptions of the sub-samples of 2011 Energy Follow-Up Survey (EFUS) that were selected to have temperature loggers and electricity consumption monitors installed.
Main heating systems (Report 4)	Presents the analysis of the data collected during the household interview on primary (main) space heating systems and usage and the results of the household heating patterns as determined from analysis of the EFUS temperature data
Secondary heating systems (Report 5)	Presents the findings on the extent and type of secondary heating and how it is used and provides an overview of the usage of these systems in the English housing stock.
Conservatories (Report 6)	Presents the results from the Interview Survey component of the 2011 Energy Follow-Up-Survey (EFUS) which collected detailed information on the percentage of conservatories and how households in England use and heat the conservatories.
Thermal comfort and overheating (Report 7)	Presents the analysis of the data collected as part of the household interview thermal comfort and overheating. It also presents the results as reported by the householder together with the information obtained from the monitored household temperatures data collected with temperature loggers.
Lighting (Report 8)	Presents results from the Interview Survey component of the 2011 Energy Follow-Up-Survey (EFUS) which collected information about the lights in three of the main rooms of the house (living room, main bedroom and kitchen), as well as lights left on overnight and outside lights powered from the household electricity supply.
Domestic appliances, cooking and cooling equipment (Report 9)	Presents the analysis on the electrical appliances and cooking such as how many appliances are in the stock, and how they are being used.
Household underspend (Report 10)	Outlines the results of analysis of the energy for heating, lighting, appliance use and cooking into the subject of household "underspend".
Methodology (Report 11)	Outlines the survey methodology used in the EFUS such as sampling, data collection weighting and data quality.

Table 3.5 gives a summary of the data collected during the EFUS survey. An appliance survey recorded the age and types of the appliances that were available in the homes. Participants were also asked detailed questions on their appliance usage patterns, such as frequency of usage and average duration of usage of an appliance, including the differences between weekdays and weekends and summer time and winter time. Furthermore, the survey included information on household water heating usage and lighting. A sub-sample of 79 homes was monitored by collecting a survey data on appliance and lighting usage. In addition, electricity, gas and water meter readings of 1,345 homes are available in the dataset.

Table 3.5 Variables that were monitored/collected in the 2011 Energy Follow-up Use Survey (EFUS)

Variable	Description
Appliance ownership	Data collected on a wide variety of appliances (including age and type etc.) and lighting (including bulb type e.g. CFL, tungsten etc.)
Type and usage patterns of the main and secondary heating systems	Main heating system, main heating fuel, secondary heating, boiler type, alternative heating and detailed information on heating behaviours of conservatories and heating patterns such as: -Which months of year? -Hours of heating? Which rooms are heated? Is the weekend vs. weekday patterns different? etc.
Water heating system and usage	Water heating system. How water usage patterns such as: -Which months of year? -Hours of heating? Which rooms are heated? Is the weekend vs. weekday patterns different? etc.
Lighting	Questions on lighting. Also a sub-sample of 79 homes had electrical profiling equipment installed collecting high frequency data on lighting usage.
Usage of appliances	Questions on usage patterns/behaviours for a wide variety of appliances and lighting. Also a sub-sample of 79 homes had electrical profiling equipment installed collecting high frequency data on appliance and lighting usage.
Gas and electricity consumption data from meter readings	Presence of electricity, gas, water meters and the meter readings from a sub sample of 1,345 homes.

3.3.3 2011 Household Electricity Survey (HES)

The links to the HES dataset were provided by the consulting company called ICF International (Inner City Fund International) in .csv format.[6] The monitored data from each household were compiled into a database. This (7.4 GB) file contains all the measured sensor data – both for electricity and temperature. There are approximately 250 million data points. The variables that were monitored and collected in the Household Electricity Use Survey are presented in Table 3.6:

[6] This data can be downloaded by sending an e-mail to efficient.products@icfi.com.

Table 3.6 Variables that were monitored and collected in the Household Electricity Use Survey

Variable	Description
Power demand	The power demand of each appliance in the household with a mix 2 and 10 minute resolution
Temperature	The internal and external temperatures of the house were monitored using thermometers.
Appliance characteristics	Brand manufacturer Model of the appliance Year of the product bought With their energy efficient ratings
Diaries	Diary data that was filled in for households' use of certain appliances. Most households completed diaries for two weeks.
Demographics & Household characteristics	Household types Household age Working status UKHES code Answers to the environmental attitude questionnaires. The Experian Mosaic Groups
Energy rating	RdSAP rating
Details of house dimension and construction	Dwelling types Floor area & window area Glazing type Insulation thickness

The electricity demand dataset is split into six files. The data files downloaded are presented in Table 3.7:

Table 3.7 HES files with a short description

File name	Description
agd-1a, agd-1b, agd-1c, agd-1d	1 = 2 minute intervals for approximately one month (226 households)
agd-2	2 = 2 minute intervals for approximately two months (for the 26 households which were monitored for a year, one month of that was in 2-minute intervals).
agd-3	3 = 10 minute intervals (bulk data for the 26 households which were monitored for a year)
appliance_codes, appliance_type_codes, household codes, ipsos_non_tabular	These files explain the number that were used as codes in the dataset for each appliance, appliance type and households
rd_sap- public_anon	Information about the dwelling types, floor area & window area, glazing type, construction of the walls
rd_sap date ranges	Years of construction of the dwellings (age band)
rdsap_energy_efficiency_rating_anon	RdSAP ratings and CO_2 emissions
ipsos-anonymised-corrected 3107	Household types, number of appliances in the house, answers to the environmental attitude questionnaires, working status, age, gender and ethnicities
rdsap_glazing_details_anon	Window area, glazing type
rdsap_insulation_thickness_anon	Insulation thickness
appliance data monitored_appl_energy_efficiency	Brand Manufacturer, model of the appliance, year of the product bought with their energy efficient ratings, the room where the appliance is situated
appliance_date_periods monitored_appl_energy_efficiency_rating	Earliest and latest dates when the monitoring starts for an appliance Energy efficiency ratings for the appliances
diary_dish_washer, diary_hob diary_oven, diary_washing machine	Diary data that was filled in for households' use of certain appliances.
heus_experianmosaicgroups	Categorisation of the 250 houses referred to as Mosaic Groups

Appliances are organised in a code scheme. Detailed data points, with the power demand of the individual appliances, can be determined with either a 2 minute or 10 minute resolution. Table 3.8 shows the number of each type of appliance that was monitored. The total number of appliances monitored was 5,860.

Table 3.8 Number of appliances monitored in the HES sample

Appliances	Number of appliances monitored in the homes
Cold appliances	Fridge-freezer (155)*, Refrigerator (113), Upright freezer (105), Chest freezer (42), Wine cooler (3), Fridge+freezer (18),
Computer site	Laptop (174), Router (139), Printer (113), Desktop (106), Monitor (103), Computer Site (49), Speakers (15), Multifunction Printer (14), Modem (12), Computer Equipment (7), Fax/Printer (5), Scanner (3), Monitor+Printer (2), Hard drive (1)
Cooking	Kettle (243), Microwave (219), Cooker (158), Toaster (68), Oven (53), Extractor Hood (42), Bread Maker (13), Coffee maker (13), Hob (13), Food Mixer (5), Grill (5), Fryer (4), Food Steamer (2), Oven+Cooker (2), Bottle Warmer (1), Hot Tub (1), Microwave+Grill (1), Yoghurt Maker (1)
Audio-visual site	Television (417), Set Top Box (187), DVD (127), Audiovisual Site (52),Nintendo Wii (46), VCR (33), TV+DVD (30), Sky Set Top Box (25), Hi-Fi (23),Sony PS3 (18), DVD+VCR (17), DVD Recorder (15), Microsoft Xbox 360 (11),Sony PS2 (10), Home Cinema Sound (9), TV+VCR (9), Game Console (2),Audiovisual Equipment (7), Radio (7), Microsoft Xbox (7), Blu-ray Player (6), CD Player (4), Video Sender (1), TV+Set Top Box (4), AV Receiver (2), TV+VCR+DVD (2), Game Console+Hifi (1), TV Booster (1), Aerial (2), TV+DVD+Set Top Box (1)
Heating/cooling	Heater (64), Central Heating (8), Circulation Pump (2), Air Conditioning (1)
Lighting	Lighting (636), Light Distribution (380)
Water heating	Shower (107), Water Heater (45), Immersion Heater (44)
Washing/drying	Washing Machine (206), Clothes Dryer (117), Dishwasher (112), Washing/Drying Machine (22)
Other	Sockets (499), Vacuum Cleaner (185), Hair Dryer (89), Iron (48),Hair Straightener (34), Fan (17), Aquarium (15), Alarm (14), Other (12), Fire (3), Sewing Machine (9), Electric Blanket (6), Pond Pump (6), Door Bell (5), Steriliser (5), Paper Shredder (4), Smoke Detectors (4), Vivarium (4),Clock Radio (3), Cordless Phone (3), Dehumidifier (3), Trouser Press (3), Hair Dryer+Hair Straightener (3), Organ (3), Alarm+Other (2), Charger (2), Massage Bed (2), Baby Monitor (1), Electric Chair (1), Jacuzzi (1), Motorhome (1), Digital Picture (1), Sunbed (1)

*The number of appliances monitored are indicated in parenthesis. For example, 155 fridge-freezers were monitored.

Households were selected by Ipsos MORI on the basis of the life-stage of the occupants. Table 3.9 shows the household types in details.

Table 3.9 Household type in the HES sample

Household types:	Name	Occupancy Number	Number of total houses
Type 1	Single Pensioner	1	34
Type 2	Single Non-Pensioner	1	35
Type 3	Multiple Pensioner	=<2…….5	29
Type 4	Households with children	=<3…….4	78
Type 5	Multiple persons with no dependent children	=<2	75

Only the occupant gender for the single person households is known. The gender distribution in the multiple occupancy households is unknown. The gender of the occupant who answered the environmental attitude questionnaire is known in the multiple persons households. The age range of the households is given, again only the age of the occupant who answered the environmental attitude questionnaire is known in the multiple occupant households. However, reports used from the EFUS dataset do not consider gender. Therefore, the division for gender is not made for HES either. Regarding income and employment, only the working status of the households is known, such as unemployed (seeking work), retired and full-time paid work. Occupants income was not surveyed.

The screenshot of the power demand records of the 2011 HES dataset is shown in Figure 3.4. The first column indicates the household ID; second column shows the appliance type (washing machine is coded as 51); third and fourth columns indicate date and time of the recording, respectively. Power demand record is shown at the last column (Power) in Watts.

Monthly washing machines

Household (ID number)	Appliance (code)	Date (yyyy-mm-dd)	Time (hh:mm:ss)	Power (Watts)
201103	51	2010-06-21	08:34:00	0
201103	51	2010-06-21	08:36:00	0
201103	51	2010-06-21	08:38:00	0
201103	51	2010-06-21	08:40:00	24
201103	51	2010-06-21	08:42:00	24
201103	51	2010-06-21	08:44:00	28
201103	51	2010-06-21	08:46:00	190
201103	51	2010-06-21	08:48:00	703
201103	51	2010-06-21	08:50:00	722
201103	51	2010-06-21	08:52:00	722
201103	51	2010-06-21	08:54:00	703
201103	51	2010-06-21	08:56:00	45
201103	51	2010-06-21	08:58:00	18
201103	51	2010-06-21	09:00:00	24
201103	51	2010-06-21	09:02:00	24
201103	51	2010-06-21	09:04:00	28
201103	51	2010-06-21	09:06:00	45
201103	51	2010-06-21	09:08:00	21
201103	51	2010-06-21	09:10:00	32
201103	51	2010-06-21	09:12:00	28
201103	51	2010-06-21	09:14:00	40
201103	51	2010-06-21	09:16:00	84
201103	51	2010-06-21	09:18:00	0

Figure 3.4 The screenshot of appliance power recording of the 2011 HES dataset: the Household ID, appliance code (51 corresponds to washing machine), date, time and power demand of the appliance in Watts.

The HES monitored a total of 251 owner-occupier households across UK. Of the 251 households surveyed, 26 were monitored for a one-year period and the remainder were monitored for periods of one month intervals throughout the year. Monthly monitored washing machines were always measured using 2 minute intervals, whereas the time resolution for the annually monitored houses is a combination of 2 minute and 10 minute intervals. The monitored period of the households with their start and end dates is presented in Figure 3.5.

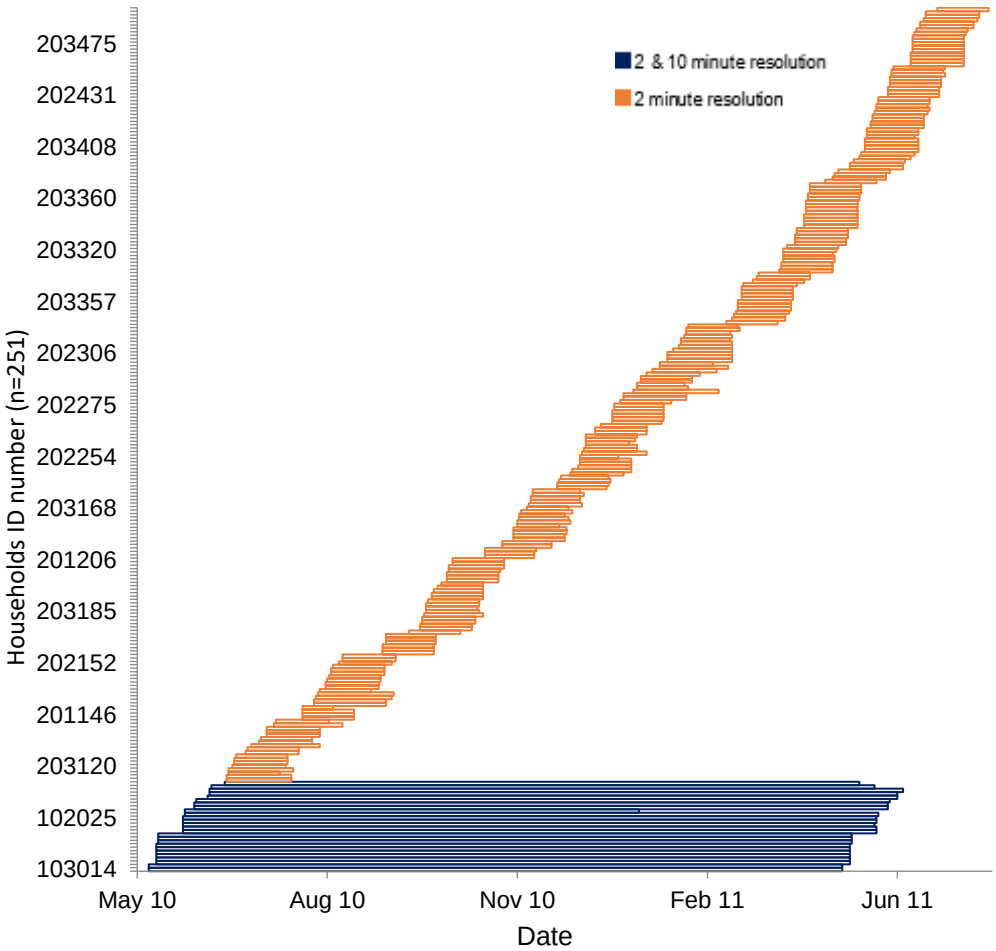


Figure 3.5 The monitored period of the households of 251 households

Figure 3.6 presents the duration of the power demand of annually monitored households' washing machines, measured using 2 and 10 minute intervals. Only annually monitored households' washing machines are shown, because the monthly monitored households' washing machines were always measured using 2 minute intervals.

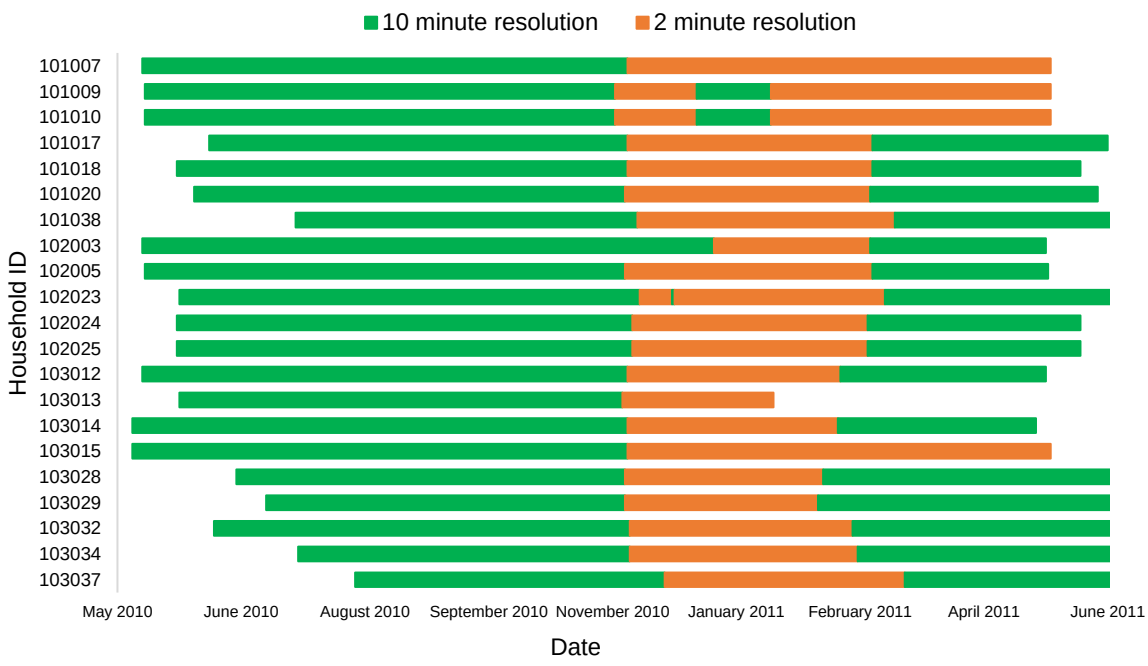


Figure 3.6 Duration of the yearly monitored washing machine at 2-minute and 10-minute resolution (For different appliances, the duration and the start times of the 2-minute and 10-minute recordings differ)

A subset of the full dataset of 251 homes was chosen as different measurement intervals were used in the survey (2 minute and 10 minute intervals). This work considers only the 225 homes which had their appliance power measurements recorded at 2 minute intervals (orange bars in Figure 3.5). This shorter time interval provides the greatest level of detail for identifying the occupant behaviours and means the subsequent analysis and modelling methods provided in this thesis were based on the same measurement interval for all homes. In Figure 3.6 the monitoring periods for the 225 homes are shown in order of start date, with the horizontal line for each home denoting the start and end of the monitoring period when appliance power measurements were taken. All monitoring took place between May 2010 and June 2011 on a rolling basis, with different homes monitored at different time periods between these dates. The homes were monitored for between 20 and 45 days, with an average monitoring period of 27.7 days.

Figure 3.7 shows the distribution of the 16 appliance types in the sample of 225 homes studied in this work[7]. Figure 3.7 shows that the most common appliance types are

[7] See Section 3.4 for why these appliances were chosen.

washing machines (n=176), followed by fridge-freezers (n=129) and electrical cookers consisting of hob, oven and grill (n=105). The least common appliance types were stand-alone electric hobs (n=9) and stand-alone electric grills (n=5). Although hobs and grills are found in the majority of UK homes, in most cases they are operated by gas rather than electricity (DECC, 2014a).

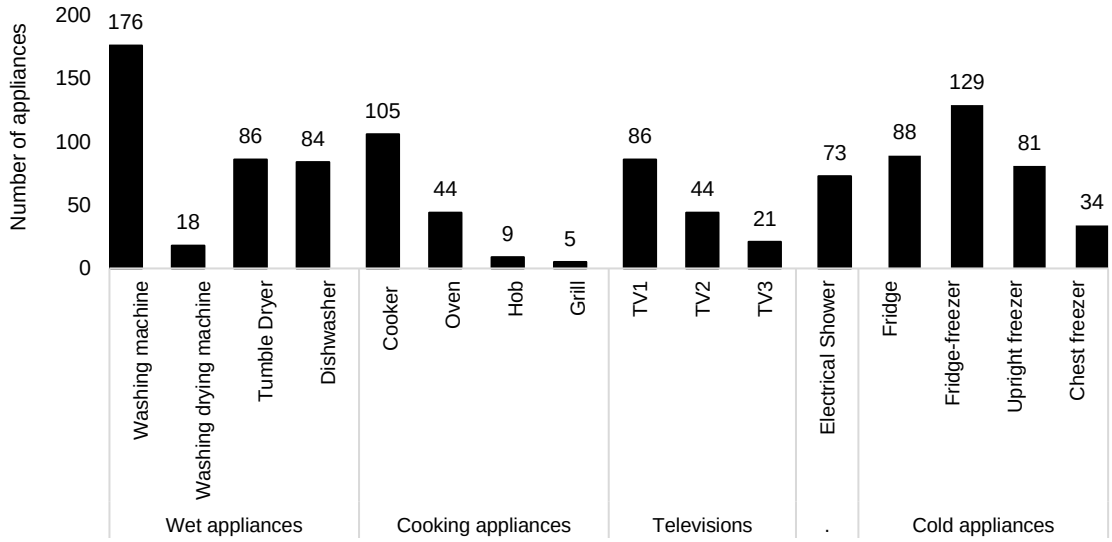


Figure 3.7. Example of appliances monitored in the HES (2011) (TV1 is the television that is most frequently switched-on, TV2 is the second most frequently switched-on television and TV3 is the third most frequently switched-on television)

Data cleaning was carried out on the 2 minute appliance power measurements prior to analysis. Visual inspection of time series plots was used to identify incorrect readings (errors) that were either too high or too low and contained errors. In some cases, readings as high as 10kW were recorded in a 2 minute interval which was clearly too high compared to the expected power demand of the appliance. 0.0006 % of the readings were identified as incorrect readings and these were removed from the dataset.

Comparing the expected and actual number of daily readings for each appliance was used to identify missing data, times when a 2 minute appliance power demand should have been recorded but was not. Missing data can often occur in monitoring studies through sensor and network errors, as well as data logging errors. In the dataset either

a few readings were dropped during a day (Figure 3.8). It is important to note that the monitoring starts in the afternoon of the first day and ends in the noon of the last day of monitoring.

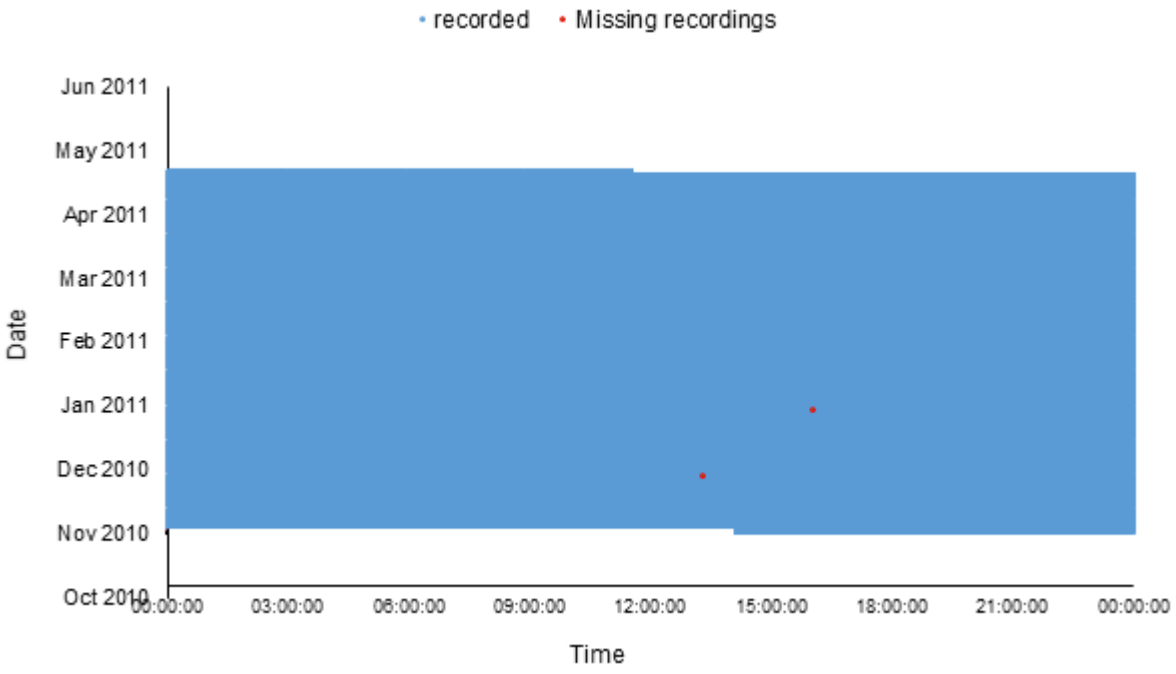


Figure 3.8 Missing 2 minute resolutions recordings household 101007

In cleaning the missing data two approaches were taken. Firstly, where there was a significant part of the day missing, those profile days were deleted so as not to distort statistics based on daily usage. This resulted in 0.006 % of the readings being deleted. Secondly, where a small number of consecutive readings were missing the missing data points were manually inserted by interpolating between the values for missing points. 0.002 % of the data was estimated in this manner. Table 3.10 presents the missing points and error values are shown in percentages with the threshold power demand for each 16 appliances used to determine the incorrect readings.

Table 3.10 Missing values and the miss recorded values in the HES dataset presented in percentages for each 16 appliances

	Appliance type	Missing values (%)	Error value (%)	Threshold Power demand (W)
Wet appliances	Washing machine	0	0	3000
	Washing-drying machine	0	0	3000
	Tumble dryer	0	0	4000
	Dishwasher	0	0.00018	4000
Cooking appliances	Cooker	0.07	0	10,000
	Oven	0	0	4000
	Hob	0	0	4000
	Grill	0	0	1500
Televisions	TV1	0	0.002	450
	TV2	0.03	0.0007	450
	TV3	0	0	450
Electric shower	Electric shower	0.004	0.00006	10,000
Cold appliance	Fridge	0	0.00005	400
	Fridge-freezer	0.07	0.00007	400
	Chest-freezer	0	0	400
	Upright-freezer	0	0.0001	400

3.3.4 Linking the datasets

A mutual household characteristic is chosen to link the three datasets to model the HAU model. Figure 3.9 shows the common characteristics of each dataset with a Venn diagram.

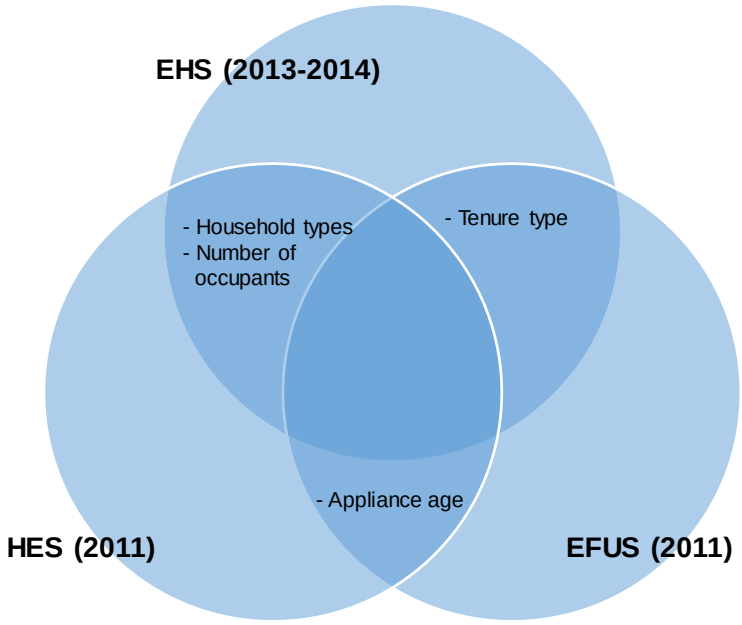


Figure 3.9 Venn diagram to show the common characteristics among the datasets used for developing the HAU model

There is no common characteristic for three of the datasets. For example, 2011 EFUS and 2013-2014 EHS datasets can be linked by tenure type such as households with “own out right”, “renting” or “mortgage” etc. However, this information is not available in the 2011 HES dataset. Similarly, household types such as “families”, or “single person” or “multiple persons” etc. are linked characteristics between EHS (2013-2014) and HES (2011) dataset, however this information is not available in the 2011 EFUS dataset.

Although the 2011 EFUS is a follow up survey of a subset of households first visited as part of the EHS 2013-2014, the link between these two dataset was not available in the UK data archives to the public in the beginning of this study (UK Data Service, 2013). Recently it has been possible to link the 2011 EFUS data to the EHS data by applying for access to SN 7883 which is subject to further access restrictions. Additionally, there is a report prepared by DECC and the Building Research Establishment (BRE) for appliance ownership (Report 9: Domestic appliances, cooking and cooling equipment) that show the division of the appliance ownership according to the household composition (DECC and BRE 2016). In this report, saturation levels of the appliances across household composition are provided. The problem of using these saturation levels is that there is no distinction between the individual appliances. For example, the saturation levels of refrigeration across the households is provided which includes fridge freezer and separate fridges together. Similarly, the saturation levels of laundry appliances across the households is provided which includes washing machines and washing-dryings machine together. Therefore, it is impossible to comment on the saturation levels of individual appliances separately such as washing machines vs washing-drying machines or fridge freezers vs. separate fridges.

The only linking variable of 2011 EFUS and 2013-2014 EHS datasets at the time of this study was “tenure type” of the households. Therefore, the model uses the common characteristics as “tenure type” for randomly populating the “EHS (2013-2014) household sample” with the appliances by using the information derived from the 2011 EFUS dataset.

3.4 CHOICE OF APPLIANCE TYPES TO MODEL

Three criteria are defined to select which appliances to be used in the HAU model. These are: i) the saturation level of appliance types in the home; ii) the appliance type's contribution to the electricity demand of the household; and iii) the suitability of the appliance type for a demand response case (demand response potential). These criteria are defined based on the literature review (Section 2.3) and are ranked as high, medium and low for appliances types.

Appliance ownership saturation levels are based on the literature review in this thesis (Table 2.4). The saturation levels of the appliances higher than 70%, between 70%-40% and below 40% are classified as high, medium and low, respectively.

The contribution of an individual appliances' electricity consumption to the total yearly household electricity demand and peak load are based on the values calculated from HES (2011) dataset. An appliance's contribution to electricity demand and peak load higher than 4%, between 2%-4% and below 2% are accepted as high, medium and low, respectively.

Demand response potential is ranked according to Table 2.6. Appliances that are categorised for demand response types of power-shiftable and time-shiftable are accepted as high demand response potential whereas appliances under demand response types of non-shiftable but curtaible and non-shiftable and non-curtaible are accepted as low demand response potential (see Section 2.3 for the definitions of demand response types mentioned above).

Table 3.11 presents a summary of the list of appliances and the ranking of them for the three criteria explained above. The average load profiles suggest that cooking, lighting and audio-visual appliances use the largest share of peak power. Washing/drying appliances and cold appliances also account for a significant share of the peak load, and these probably offer more potential for changing the times of use.

In Table 3.11, the contribution of appliances to the electricity demand is presented as the percentage of the appliance electricity demand to the total of all other electrical appliances including lighting. However, this percentage decreases when electric space heating and water heating are included.

Table 3.11 List of appliances and ranking for the three criteria

Appliance category	Appliances	Saturation level[1]	Contribution to the electricity demand (%)	Contribution to the peak demand	Demand response potential	Will it be modelled ?
Wet appliances	**Washing machine**	High (97%)	Medium (2.9%)	High (M) [2]	High	Yes
	Tumble dryer	High (62%)	High (7.0%)	High (E)	High	Yes
	Dishwasher	Medium (41%)	High (5.2%)	High (E)	High	Yes
	Washing-drying machine machine	Medium (37%)	High (4.3%)	High (E)	High	Yes
Cooking appliances	**Microwave**	High (80%)	Low (0.8%)	Low	Low	No
	Cooker	Medium (48%)	High (5.6%)	Medium (M,E)	Low	Yes
	Electrical hob	Medium (38%)	High (4.2%)	High (E)	Low	Yes
	Electrical oven	High (69%)	High (4.2%)	High(E)	Low	Yes
	Electrical grill	High (70%)	High	High(E)	Low	Yes
	Aga Rayburn style cooker	Low (5%)	Low	Low	Low	No
	Kettle	High (99%)	Medium (2.4%)	Low	Low	No
Televisions		High (97%)	Medium (2.8%)	High	Low	Yes
Electrical shower		Medium (40%)	High (5.1%)	Low	High	Yes
Cold appliances	**Separate Fridge**	Low (19%)	Medium (2.9%)	Medium (M,E)	High	Yes
	Fridge freezer	High (46%)	High (7.5%)	Medium (M,E)	High	Yes
	Separate freezer[3]	High (65%)	High (11.1%)	Medium (M,E)	High	Yes

[1] Numbers in the parenthesis represent the percentage of saturation levels of appliances. (97) mean 97% of the homes have washing machines
[2] M and E represents morning and evening peak, respectively.
[3] In the HES dataset; freezer is separated into chest freezer and upright freezers; these two appliances will be modelled under the appliance type of freezer.

Drawing conclusions from Table 3.11, the HAU model will model 16 appliance types existing in the households. These 16 appliance types were chosen based on having “high” levels for the criteria described before. These appliance types have a significant impact on building electricity demand and represent, on average, 75% of the appliance electricity consumption in a UK home (DECC, 2014a). As indicated in the footnote, separate freezers are modelled as upright freezers and chest freezers depending on the value of the HES dataset. In addition, up to three televisions are modelled as TV1, TV2 and TV3. TV1 is most frequently switched-on television in the household, TV2 is the second and TV3 is the third most frequently switched-on television in the household.

3.5 DEVELOPING THE HOUSEHOLD APPLIANCE USAGE MODEL

3.5.1 Identifying appliance behaviour metrics in the monitored data

The term ‘appliance behaviour’ is defined here as a combination of occupant behaviour and the operating characteristics of the appliance itself. In some cases an appliance behaviour is directly driven by the occupant behaviour (e.g. switching on a television), in other cases appliance behaviour is determined solely by the appliance (e.g. a fridge cycling on and off when the occupants are not at home) and in some cases a combination of both occupant behaviour and appliance characteristics determine the appliance behaviour (e.g. the duration of a washing machine cycle is determined by both the user’s choice of programme cycle and the make and model of the machine itself).

In this work three appliance behaviour metrics are proposed to describe the behaviour of household electrical appliance use: i) the number of switch-on event that occur over a specified time period (e.g. a day or a month); ii) the time of day when the switch-on events occur and iii) the duration of appliance use (the length of time that the appliance is switched on for). Table 3.12 summarises the appliance behaviour metrics chosen for this study based on the literature review (Section 2.3.2) and includes the metric definitions, to which appliance type they are applied, and the occupant behaviour and appliance characteristics influencing factors.

Table 3.12 Appliance behaviour metrics chosen

Appliance behaviour metric	As applies to:	Definition	Occupant behaviour influencing factors	Appliance characteristics influencing factors
Metric 1: Number of switch-on events	- Wet appliances, TVs, cooking appliances, electric showers	- The number of times in a specific time period that the appliance is switched on	- Occupancy patterns and occupant use of appliances	- None
	- Cold appliances	- The number of times in a specific time period that the compressor switches on	- The occupant setting of the internal thermostat, number of times the door is opened, amount of contents (food) in the appliance	- Appliance's own cooling mechanism for temperature control
Metric 2: Switch-on time of day	- Wet appliances, cooking appliances, TVs, electric showers	- The time of day when the appliance is switched-on by the user	- As above	- None
	- Cold appliances	- The time of day when the compressor switches on	- As per 'switch-on number' above	- As above
Metric 3: Duration	- Wet appliances	- The length of time which the chosen appliance cycle runs	- Choice of cycle, amount of clothes/dishes placed in device	- Impact of model/brand of appliance on cycle duration, cold water feed temperature
	- Cooking appliances, TVs, electric showers	- The length of time until the user switches off the appliance.	- Occupancy patterns and occupant use of appliances	- None
	-Cold appliances	- The length of time which the compressor runs for	- As per 'switch-on times' above	- Impact of model/brand of appliance

The three appliance behaviour metrics are inferred from the 225 HES households using the monitored 2-minute power demand measurements. Figure 3.10 shows the examples of the power demand measurements for three appliance types: i) washing machine cycle (type of programme that the washer uses) with the high peak at the start of the cycle and an increase at the end of the cycle whilst spinning; ii) TV1 uses with constant power demand levels and; iii) the cycling operation of a fridge freezer. Figure 3.10 illustrates the identification of the switch-on and switch-off times with black arrows where the appliance is switched-on at a particular time i.e. increase in power demand from 0 W to a higher value. Further information on method for the identification is provided at Table 3.13.

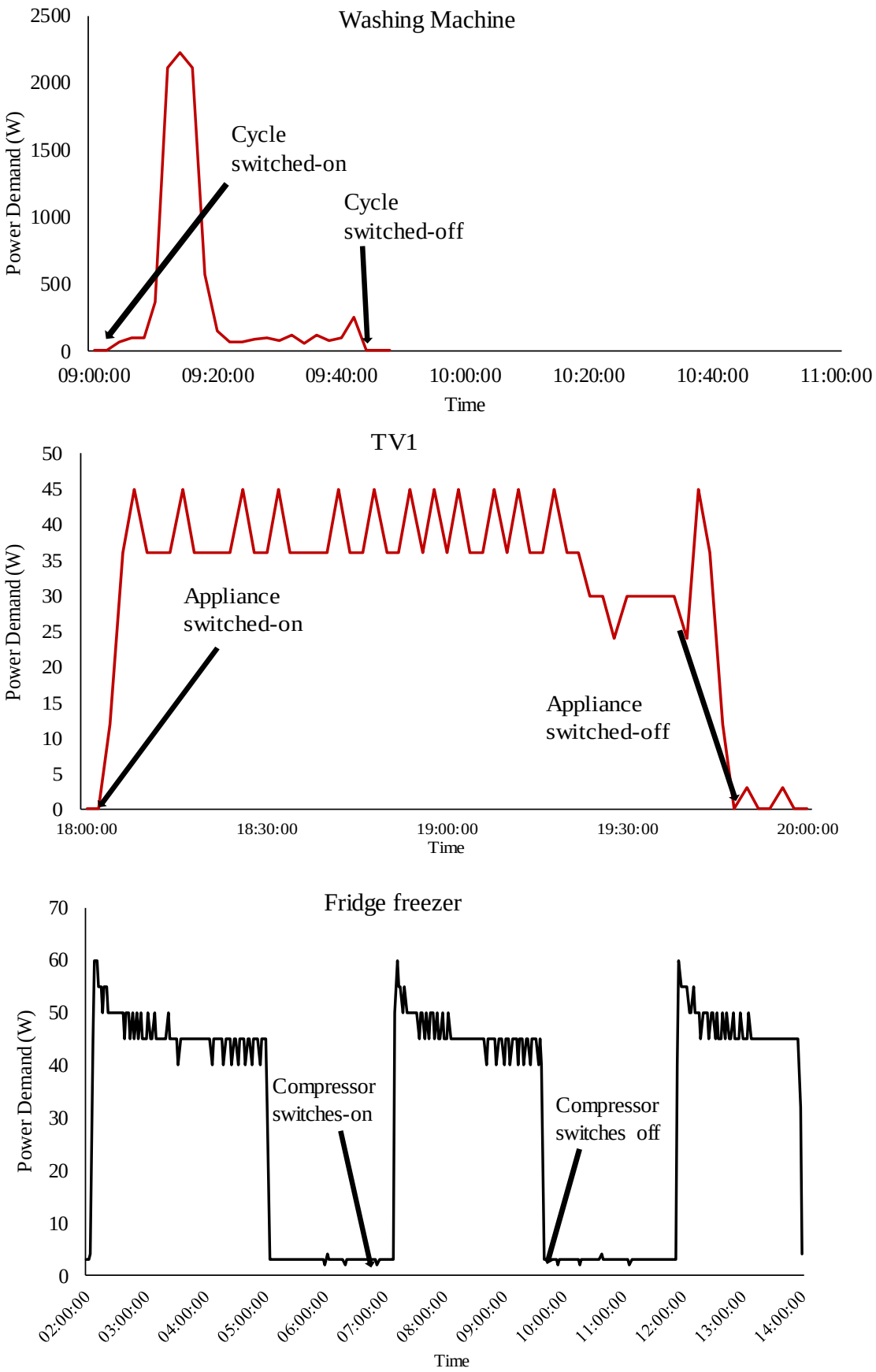


Figure 3.10.Identifying the switch-on times (e.g. start of the cycle/activity), switch off times (e.g. end of the cycle/activity) of washing machines (top), televisions (middle) and fridge freezer (bottom).

Table 3.13 summarises methods of the identification of switch-on and switch-off events and the appliance behaviour metrics. To identify the appliance behaviour metrics firstly switch-on events and switch-off events must be identified. Once the switch-on and switch-off events had been identified from the measured data, the three appliance behaviour metrics were calculated for each appliance in the dataset.

Table 3.13. Method for the identification of switch-on, switch off moments and the calculation of the appliance behaviour metrics

Identification of…	Description	Method
Switch-on events	Occurs at the time step when the power reading changes from maximum standby power (3 Watts)[1] or off mode (0 Watts) to minimum higher power reading (6 Watts).	For wet appliances, the switch-on moments are determined through visual data inspection. For rest of the appliances, an algorithm is configured to detect time step when the switch-on occurs.
Switch-off events	Occurs at the time step when the power reading changes from maximum standby power (6 Watts) or higher (on-mode) to 3 Watts or lower (off- or standby- mode)	For wet appliances, the switch-on moments are determined through visual data inspection. For rest of the appliances, an algorithm is configured to detect time step when the switch-on occurs.
Number of switch-on events	Identified by summing up the number of switch-on events of the appliance in a period	Calculated by code once the switch-on events and switch-off events are identified
Switch-on time	The time step when the switch-on event occurs	Taken as the time step when the switch-on event occurs
Duration	The time interval between the switch-on moment and end of the usage (either stand-by mode or off-mode).	Duration is calculated by code once the switch-on and end of the usage are identified.

[1] The monitoring equipment records power levels at 3 W intervals (DECC, 2014a) and a reading of less than 3 W is taken as a reasonable assumption that an appliance is on standby mode or off-mode.

3.5.2 Statistical analysis of variation between household types using ANOVA

Several studies in the literature found that there is a variation in the number of switch-on events, switch-on times and duration length of appliance usage across household types, occupant number, days of the week and seasons (Section 2.4.2). To test the significance of this variation in the HES dataset a number of statistical approaches are required. This section introduces the statistical techniques used.

The variation of occupant behaviour was tested between more than two groups in order to determine if it was significant. For example, household types have five groups, occupant numbers have six groups and days of the week have seven groups (Table 3.9). Analysis of variance (ANOVA) is an established and robust technique for testing for statistical differences between the means of samples when more than two groups are present (Field, 2005). ANOVA has been used in energy studies (Guerra-Santin & Itard, 2010) and in temperature studies (French et al., 2007).

ANOVA is a measure of how much of the total variances comes from the variance between groups or variance within groups (McKillup, 2006). Testing for statistical significance using ANOVA has a number of assumptions about the data which are i) the samples are normally distributed; ii) the samples have equal variance; and iii) samples are selected at random.

ANOVA returns an F-ratio calculated by the following equation.

$$F = \frac{variance\ between\ the\ groups}{variance\ within\ the\ group} \qquad \text{Equation 3.1}$$

SPSS was used to run the one-way ANOVA test. First of all, Levene's test is performed in order to test the homogeneity of variances. If the p-value of the Levene's test is less than 0.05, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances of the samples in the population and the ANOVA is not performed as it violates one of the assumption of ANOVA. If this is not the case, the ANOVA test is performed and it returns F-ratio which is then looked up in a table of f-distributions based on the number of degrees of freedom to find the level of significance. Where the significance level is less than 0.05 there is a 95% chance that there is a genuine difference between at least two of the groups.

It is important to note that a significant result ($\alpha < 0.05$) from an ANOVA test does not indicate whether there are statistically significant differences between the means of all of the groups, only that there is a difference between at least two of the groups. For example, it may be the case that the only statistical differences occur between single

household with pensioner and multiple occupants' households. Therefore, a further test called a "Post-hoc" should be performed to see which groups have significant differences. The ANOVA test results are shown in Section 4.2 for each behaviour metric.

3.5.3 Methods for developing the appliance behaviour model

In this section, the stochastic model of Household Appliance Usage (HAU) model is developed. The HAU model simulates the occupants' use of appliances within multiple homes over a chosen time period. The model works as follows:

- The buildings to be modelled and the appliances within each building are specified. For example, Household 1 with washing machine, dishwasher, cooker etc., Household 2 with washing machine, tumble dryer, grill etc. In this work, 225 households with 176 washing machines, 18 washing-drying machines etc. are specified which are identical to HES dataset as presented in Figure 3.5.
- A time period for the simulations is chosen. (27 days for Household 1, 28 days for Household 2 etc.)
- For each appliance, the model calculates the three appliance behaviour metrics as follows:
    1. The number of switch-on events that occur for each day in the monitoring period
    2. The time of day when each of these switch-on events occur
    3. The duration of each occurrence of an appliance use following a switch-on event.

The HAU model uses probability density functions (PDF) and cumulative distribution functions (CDF) to implement a stochastic modelling process. As a result, the model generates different final results each time it is run and thus running the model multiple times can give information on the distribution of each of the appliance behaviour metrics. Figure 3.11 shows a schematic of the general modelling approach for calculating the occupant behaviour metrics within the HAU model. The simulation results are shown in Chapter 4.

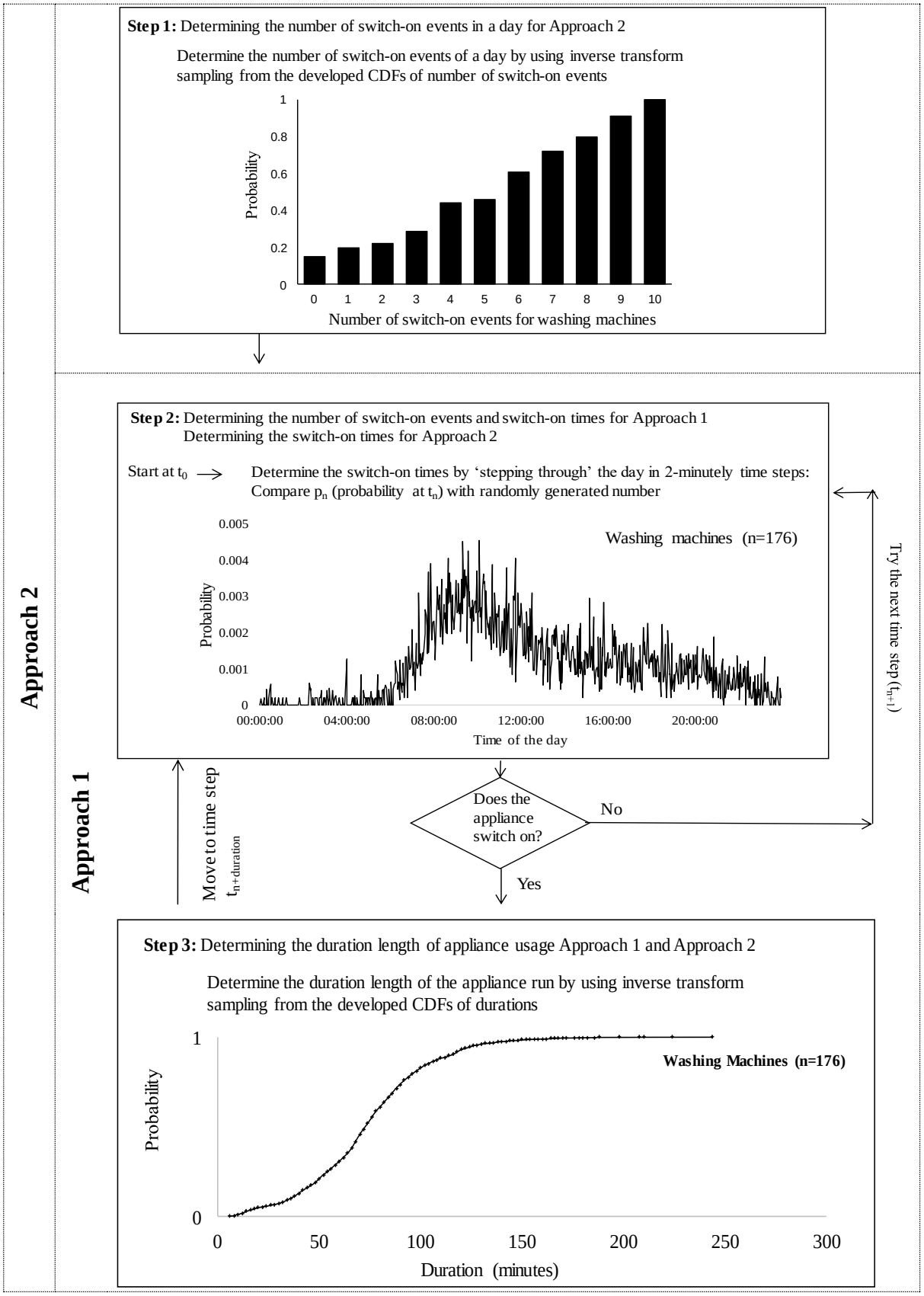


Figure 3.11 Schematic of modelling the appliance behaviour metrics in the HAU model

Three steps are shown in the Figure 3.11. Step 1 shows a cumulative distribution function (CDF) which indicates the probabilities associated with different numbers of switch-on events from the HES measurements (based on the results of calculating Metric 1 in Table 3.13). It is used to estimate the number of switch-on events which occur in a single day. The CDF can be calculated either as a CDF for each household with a particular appliance type (i.e. 176 CDFs representing each household with washing machines in the HES dataset) or it can be the CDF based on an average household (i.e. one CDF based on averaging 176 households with washing machines in the HES dataset). In Figure 3.12, an example is given for the CDF of number of switch-on events of washing machines in an average household in the HES sample. Individual CDFs of number of switch-on events based on individual households can also prepared which results 176 of CDF graphs.

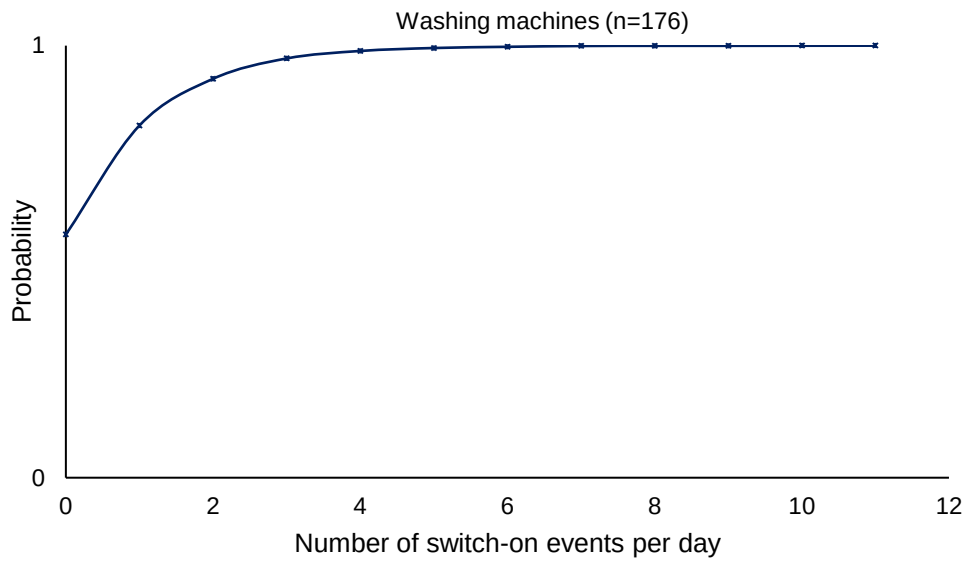


Figure 3.12 Cumulative distribution function (CDF) of number of switch-on events per day for washing machines for an average HES household

For each day in the time period of the simulation, the CDF is used to calculate the number of switch-on events in that particular day. Inverse transform sampling is used to derive the number of switch-on events of the developed CDFs. In the inverse transform algorithm, uniform random deviates are sampled (i.e. random numbers between 0 and 1) and each random number is compared against the table of cumulative probabilities. The first outcome for which the random deviate is smaller

than (or equal to) the associated cumulative probability corresponds to the sampled outcome.

Step 2 shows a probability density function (PDF) which is constructed from the HES measurements (Metric 2) and is used to estimate the time of day when a switch-on event occurs. Again this can be calculated either as an average for all households with a particular appliance type or for an individual household. For each time step, the switch-on time probability would be the sum of measured "switches on" events observed divided by the total number of time steps of the day. Each time step of a day is associated with a value between 0 and 1 corresponding to the probability of switching that appliance on at that time of day. Probability at time step (i) is calculated as such:

$$p_{i,start} = \frac{number\ of\ events\ when\ the\ appliance\ was\ switched\ on}{number\ of\ observations * total\ time\ steps\ of\ the\ day} \qquad \text{Equation 3.2}$$

In Figure 3.13, an example is given for a PDF of switch-on times of washing machines for an average household calculated by equation 3.2 (number of switch-on events observed from 176 washing machines divided by the number of observations in the dataset). Individual PDFs of switch-on times based on individual households can also prepared which results in 176 of PDF graphs.

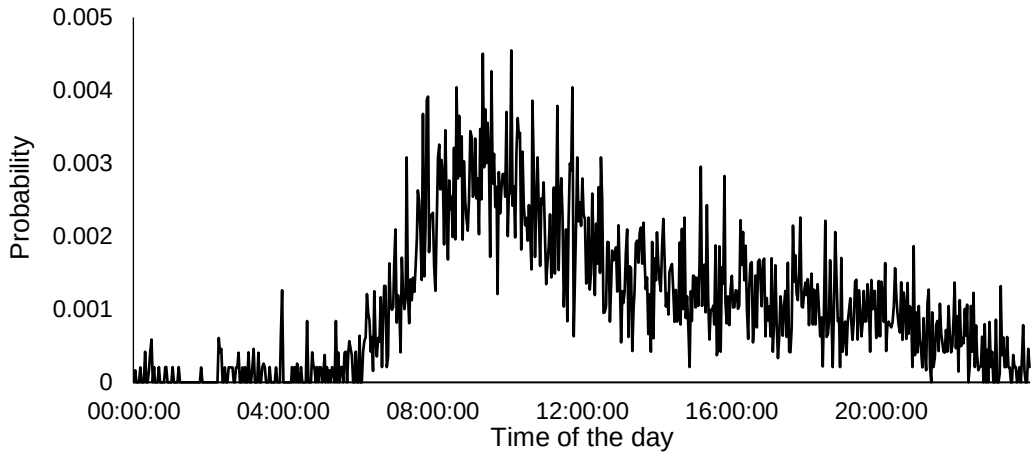


Figure 3.13 Hourly probability density function of washing machines of 176 homes

Step 3 shows another CDF which is constructed from the HES measurements (Metric 3) and is used to estimate the duration of an appliance use. Similar to CDF of daily number of switch-on events, the CDF of duration can be calculated either as a CDF for each household with a particular appliance type (i.e. 176 CDFs representing each household with washing machines in the HES dataset) or it can be the CDF based on an average household (i.e. one CDF based on averaging 176 households with washing machines in the HES dataset).

Two approaches to modelling the occupant behaviour metrics are tested. Approach 1 takes a simple approach often used in appliance behaviour modelling where the metrics are calculated using only Step 2 and Step 3. In Step 2 switch-on events are determined by 'stepping through' the day in 2-minutely time steps. For the first time step a uniform random number is generated and the appliance is switched on if the generated value is smaller or equal to the probability given by the PDF at that time step. If a switch-on event does not occur, then the process steps to the next 2-minute time step and the test for a switch-on event is repeated. If a switch-on event does occur, then the duration of the use of the appliance is calculated using Step 3. A second uniform random number is generated and is used to calculate the duration by reading the duration in the CDF of Step 3 which corresponds to the cumulative probability given by the random number. Inverse transform sampling is used to derive the duration of the appliance run from the developed CDFs in Step 3. Once the appliance run has completed, Step 2 continues at the next time step following the end of the appliance run.

Approach 2 takes a different approach designed to improve the modelling of the number of switch-on events (i.e. Metric 1) and uses Steps 1, 2 and 3 in its calculations. Step 1 is used to calculate the number of switch-on events which occur on each day. Inverse transform sampling is used to derive the number of switch-on events from the developed CDFs in Step 1. Once this is completed, Step 2 is used to calculate the time of day when each of the switch-on events occur by 'stepping through' the PDF until the model gives the number of switch-on times determined by Step 1. Step 3 is used to estimate the durations of the use of the appliance in a similar manner to Approach 1.

Table 3.14 shows the different variations of the HAU model which are used to generate the results in this thesis. The two approaches are used, Approach 1 (Steps 2 and 3 in Figure 3.11) and Approach 2 (Steps 1, 2 and 3 in Figure 3.11). For each approach, three variants are tested based on the method of constructing the PDF for Step 2 and CDFs for Steps 1 and 3. Model variants starting with 'AvgHs' use the average household CDFs and PDFs for the calculations, whereas 'IndHs' denotes the use of an individual household CDF and PDF. The individual household CDF and PDF are assigned to the building at the start of the modelling session and remain constant through the simulation. Model variants ending with 'AvgApp' use an average appliance CDF to calculate durations and with 'IndApp' use individual appliance CDFs. The average (Avg) indicate the PDFs and CDFs were developed as a single PDF or CDF representing an average of all households or appliances, whereas individual (Ind) were developed for each household/appliance, resulting in several PDFs and CDFs (176 washing machine duration CDFs or 105 cooker switch-on PDFs). These model variants were developed in order to test the effect of averaging the data on representing the diversity in occupant behaviour.

Table 3.14 HAU model variants for two main approaches described with their methods

Approach type	Variant	Calculation method for:		
		Metric 1. Number of switch-on events	**Metric 2. Switch-on time of day**	**Metric 3. Duration**
Approach 1	AvgHs_AvgApp	-	Calculated using Step 2 PDF based on an average household	Calculated using Step 3 CDF based on an average appliance
	AvgHs_IndApp	-	Calculated using Step 2 PDF based on an average household	Calculated using Step 3 CDF based on an individual appliance
	IndHs_AvgApp	-	Calculated using Step 2 PDF based on an individual household	Calculated using Step 3 CDF based on an average appliance
Approach 2	AvgHs_AvgApp	Calculated using Step 1 CDF based on an average household	Calculated using Step 2 PDF based on an average household	Calculated using Step 3 CDF based on an average appliance
	AvgHs_IndApp	Calculated using Step 1 CDF based on an average household	Calculated using Step 2 PDF based on an individual household	Calculated using Step 3 CDF based on an individual appliance
	IndHs_AvgApp	Calculated using Step 1 CDF based on an individual household	Calculated using Step 2 PDF based on an average household	Calculated using Step 3 CDF based on an average appliance

The model is developed for 16 appliance types. One-way ANOVA test was conducted to compare the effect of household type, occupant number and day types on the mean of average daily number of switch-on events, switch-on times and duration. For several appliances, ANOVA is not performed as it violates one of the assumptions of ANOVA homogeneity of variances. Some of the appliances have too small sample sizes. For the rest of the appliances, the ANOVA test results show that there is no significant effect of these characteristics on the average daily number of switch-on events. Therefore, there is no sub population for household types, occupant number nor day types is considered. 225 households have been generated exactly the same with monitoring period in Figure 3.11 by applying the HAU model procedure (e.g. 176 households with washing machines for 27 days; 84 households with tumble dryer for 28 days etc.). Each variant is run 100 times to generate the results in Chapter 4. The simulation results are shown by taking the average values of 100 simulation runs. The ability of the HAU model to recreate the patterns observed in the monitored dataset is compared. Therefore, the monitored data is not divided into training and test sets in order to prevent the bias when comparing the approaches.

3.5.4 Converting the occupant behaviour model to electricity power demand profiles

When identifying the appliance power demand during usage for each time an appliance is used, the same assumptions are made as for identifying the appliance behaviour metrics (see Table 3.13). Power demand during usage corresponds to the power (Watts) recorded during the usage of the appliance. For example, in the case of wet appliances, the power demand during usage is manually extracted from the HES dataset to ensure the correct power demand profiles are used. The power demand profiles are assumed to be constant for cold appliances during compressor run. This is done to make the algorithm run faster to derive the constant power demand. An algorithm developed in Matlab calculates the average power for cold appliance sequences. For the cooking appliances, televisions and electric showers, an algorithm is developed to extract the power demand during usage. Here, simply the term “power demand” will be used instead of using the term “power demand during usage”.

Power demand is assigned simultaneously with the duration of each occurrence of an appliance use following a switch-on event in Step 3. The values of the power demand profiles are determined from the same CDFs of durations which are accompanied with a power demand profile. For example, when a time duration of 30 minutes for a washing machine is assigned from the CDF, a power demand profile for this use is assigned. For cold appliances, time duration is assigned following a switch-on event in Step 3 and constant power is assigned for each time-step for this duration. The simulation results of this section are presented in Chapter 5.

3.5.5 Methods of assigning appliance ownership

This research adopts a stochastic approach when modelling appliances in the households by randomly populating the “EHS household sample” and does not assume a fixed number and type of appliances as majority of the studies did in literature (see Section 2.4.2). This is important in calculating the demand response potential because, by assuming that everyone has identical appliances, this means people are assumed to have the same potential for demand response, which is not the case in reality (see Section 2.3.1).

The number of appliances, type and age of appliance are modelled because this information is available in the 2011 EFUS and HES datasets for a majority of the appliances. The size of the appliance (only available for TVs, representing the size of the TV screen), and energy labels and models (only available for cookers) are not modelled since the datasets are largely missing this information.

Three methods are studied to assign the appliances stochastically to the “EHS household sample”. A summary of the steps to model the assignment of appliance ownership to the household sample is explained in Table 3.15.

Method 1 assigns a complete whole household set of appliances randomly from the 2011 EFUS dataset linking the appliance sets to the 2013-2014 EHS household sample, using the household characteristics that are common to both datasets. The common characteristics was tenure type. The inverse transform sampling is used to select the whole appliance set from a given cumulative distribution function. Details of the inverse transform sampling was given in Section 3.5.3.

Method 2 assigns appliances individually and independently using the saturation levels of the 2011 EFUS dataset linking the appliances individually and independently to the 2013-2014 EHS household sample, using the household characteristics that are common to both datasets. The common characteristics was tenure type. Inverse transform sampling was used to select the number and type of individual appliances to be found within the household. This was done using the saturation levels of the individual household appliances, derived from 2011 EFUS and 2011 HES datasets, and applied as probability of availability[8] to create an individual set for each household.

Method 3 assigns appliances individually with some dependencies (ownership of a tumble dryer depends on the ownership of a washing machine) linking the appliances individually and dependently to the 2013-2014 EHS household sample, using the household characteristics that are common to both datasets. The household characteristic which this is linked to is tenure type. Method 3 follows the exact procedure of Method 2 (Inverse Transform Sampling) to assign appliance ownership (saturation levels of the individual household appliances are also derived from 2011 EFUS and 2011 HES datasets). The only difference is that the appliances are modelled on condition that other appliances exist in the household. The dependencies were calculated from the 2011 EFUS dataset. The results of the calculations are presented in Section 6.1. The dependencies of two appliances are considered (washing-drying machine and tumble dryer).

[8] This term is firstly defined by Walker and Pokoski (1985). Probability of availability is defined as the appliance saturation level in percentages. For example, the saturation level of washing machines in UK is 99% which corresponds to probability of availability of 0.99.

Table 3.15 The basic steps used to model the appliance ownership for three methods studied in this work

Methods	Step 1 Linkage	Step 2 Input	Step 3 Empirical cumulative distribution function (CDF)	Step 4 Modelling
Method 1: Assigning whole appliance sets	Determine the linking household characteristics between datasets	The number of appliance sets for each characteristic from 2011 EFUS dataset	Fits an empirical CDF for the appliance set for each composition of household characteristics.	Inverse transform sampling is applied to select the appliance set from the given CDF.
Method 2 Assigning individual appliances independently	Determine the linking household characteristics between datasets	The saturation levels of appliance types from the 2011 EFUS dataset	Fits an empirical CDF derived from the saturation levels of individual appliances is fitted for each composition of household characteristics.	Inverse transform sampling is applied to select the number and type of appliances from the given CDF.
Method 3 Assigning individual appliances dependently	Determine the linking household characteristics between datasets	The saturation levels of appliance types and the dependencies are calculated from 2011 EFUS dataset.	Fit an empirical CDF derived from the saturation levels for individual appliances are noted for each composition of household characteristics making sure that dependencies among the appliances are included.	Inverse transform sampling is applied to select the number and type of appliances from the given CDF.

Figure 3.14 shows the dependency conditions in which the probability of availability of a washing-drying machine is calculated depending on the availability of the washing machine used in Method 3. For example, the probability of availability of a washing-drying machine is lower if there is already a washing machine in the home. Condition 1 is the condition in which the availability of the washing-drying machine is calculated if there is a washing machine in the house. In other words, the proportion of the households with washing-drying machines and washing machines to those households with only washing machines is calculated. Condition 2 is the condition in which the availability of the washing-drying machine is calculated if there is not a washing machine in the house. In other words, the proportion of households without washing machines but with washing-drying machines to those households without a washing machine is calculated. The results of the calculations are presented in Section 6.1.

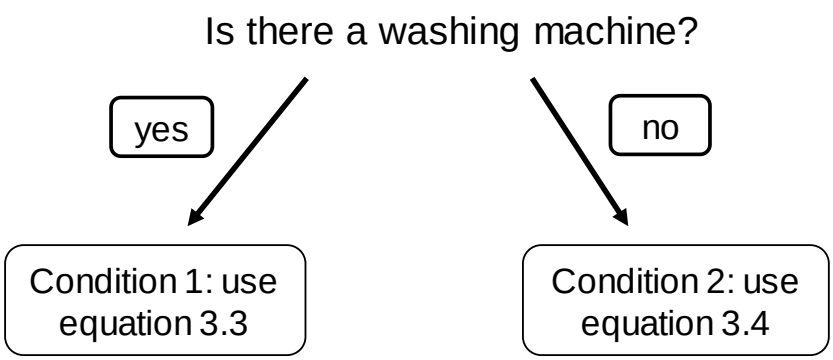


Figure 3.14 Calculation of the dependency of having a washing-drying machine as part of a washing machine

The formula for calculating the probability of availability of washing-drying machines for Condition 1 and Condition 2 are given in equation 3.3 and 3.4, respectively.

Condition 1

$$\frac{\textit{Households with washing machines and washing drying machines}}{\textit{Households with washing machines}} * 100 = \%$$ Equation 3.3

Condition 2:

$$\frac{\textit{Households without washing machines but with washing drying machines}}{\textit{Households without washing machines}} * 100 = \%$$ Equation 3.4

Similar rules have been applied to tumble dryers, however tumble dryers have dependencies on two appliances: washing machines and washing-drying machines. Table 3.15 shows the dependency conditions in which the probability of availability of a tumble dryer is calculated depending on the availability of the washing machines and washing-drying machines used in Method 3.

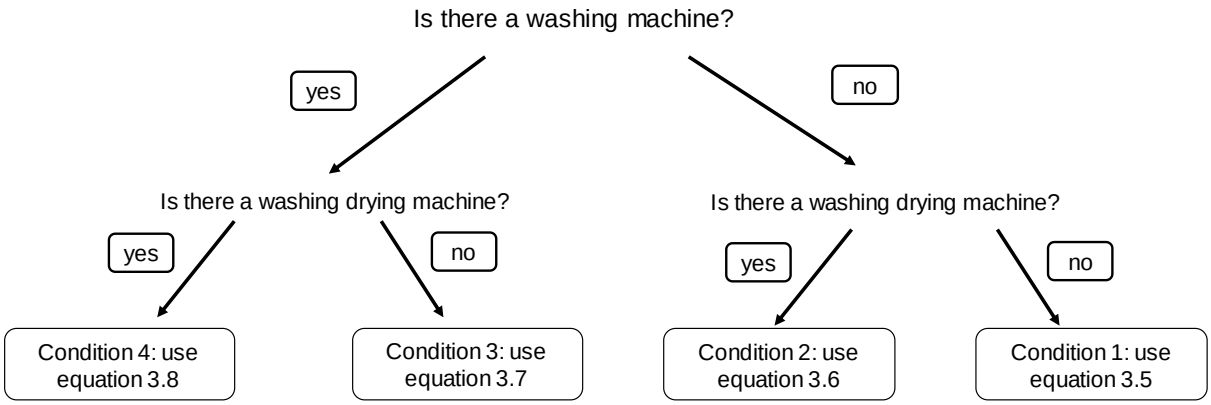


Figure 3.15 Calculation of the dependency of having tumble dryers as part of washing machine and washing-drying machines

The formula for calculating the probability of availability of washing-drying machines for Condition 1, Condition 2, Condition 3 and Condition 4 are given in equation 3.5, 3.6, 3.7 and 3.8 respectively.

Condition 1:

$$\frac{\textit{Households without washing machines and washing drying machines but with tumble dryers}}{\textit{Households without washing machines nor washing drying machines}} * 100 = \%$$

Equation 3.5

Condition 2:

$$\frac{\textit{Households without washing machines,with washing drying machines and tumble dryers}}{\textit{Households without washing machines but with washing drying machines}} * 100 = \%$$

Equation 3.6

Condition 3:

$$\frac{\textit{Households with washing machines and tumble dryers, without washing drying machines}}{\textit{Households with washing machines but without washing drying machines}} * 100 = \%$$

Equation 3.7

Condition 4:

$$\frac{\textit{Households with washing machines, washing drying machines andand tumble dryers}}{\textit{Households with washing machines nor washing drying machines}} * 100 = \%$$

Equation 3.8

The screenshot of the appliance ownership model is shown Figure 3.16. As explained in the method, appliances characteristics including age (if available).

Household	Washing machine	WM age	Washing drying machine	WDM age	Tumble dryer	TD Age	Dishwasher	DW Age	Fridge-freezer	Fridge freezer age	Electric Hob	Electrical Grill
1	1	5	0	5	0	0	0	0	1	5	1	1
2	1	7	0	7	1	6	0	0	1	7	1	1
3	1	1	0	1	1	7	1	6	0	0	1	0
4	1	3	0	3	1	4	1	4	1	2	1	1
5	1	6	0	6	1	7	1	7	1	4	1	1
6	1	2	0	2	0	0	0	0	1	3	1	1
7	1	6	0	6	1	7	1	4	0	0	1	1
8	1	2	0	2	1	5	1	2	1	2	0	0
9	0	3	1	3	0	0	0	0	1	4	1	1
10	1	3	0	3	1	4	0	0	1	4	1	1
11	1	3	0	3	0	0	1	2	1	3	1	0
12	1	4	0	4	1	3	0	0	0	0	1	0
13	1	2	0	2	1	7	1	4	0	0	1	1
14	1	4	0	4	1	4	1	4	0	0	1	1
15	1	5	0	5	1	7	1	7	1	7	0	1
16	1	5	0	5	1	3	1	1	0	0	1	0
17	1	4	0	4	1	2	0	0	0	0	1	1
18	1	4	0	4	0	0	0	0	1	4	1	0
19	1	7	0	7	1	3	1	7	1	7	0	1
20	1	2	0	2	0	0	1	3	1	3	0	0

Figure 3.16 A screenshot of the output of the appliance ownership model (the numbers for the appliance indicates the number of that appliance, 1= there is only one washing machine, 0=that appliance is not available in the household; number for the appliance age indicates the age of the appliance, WM age= 5 means the washing machine is 5 years old)

3.6 VALIDATION OF THE MODEL

The 2011 HES dataset is used to both develop and validate the model. In this study, the modelling ability in regenerating the patterns of monitored datasets is compared and therefore, the monitored data is not divided into training and test sets in order to prevent bias when comparing the modelling approaches. Often, the performance of models is compared at building level or for aggregate populations in previous studies (Paaetero and Lund, 2006; Wilké et al. 2013). However, the performance of these existing models has not been evaluated at the appliance level which is crucial for a robust bottom-up approach.

The model ability of the HAU model to regenerate the patterns of the measured dataset was compared at an individual appliance level. The simulation results were generated by taking the average values of 100 simulation runs. Simulated and measured values were compared by observing the following properties for each of the 16 appliances:

- Appliance behaviour metrics: the number of switch-on events, switch-on times and duration length of each appliance use
- The variation in appliance behaviour metrics
- Power demand profiles at appliance level (power demand vs. time of the day)
- Total power demand profiles (power demand vs. time of the day)

A second internal validation method can be used, k-fold cross-validation, which is a method commonly used to validate the performance of a model when there is no external data available (Page, 2007; Schweiker et al., 2012; Wilké, 2013, Wolf et al., 2015). This method is specifically developed to compensate for the lack of external data by estimating how well the model generalises on independent data sets. The predictive accuracy of internal data is studied using part of the dataset as a training set for model calibration and the remaining part as a validation set. The process is repeated k times for each data point, selected once in the validation set and k – 1 times in the training set. However, in this study, therefore, cross validation (where the monitored data is divided into training and test sets) could not be performed. The HES household sample was too small to perform the cross-validation (only 5 hobs in some households, 18 washing-drying machines). Therefore, splitting this dataset up into separate "training" and "testing" datasets is questionable if the goal is to test generalisation across homes.

The simulation results of the HAU model were compared with external data. These studies are the “ECUK” (BEIS,2016) and power demand profiles calculated from the Elexon Ltd (Elexon, 2016). The results of these comparisons are presented in Chapter 6.3.

3.7 APPLICATION OF THE MODEL: DEMAND RESPONSE

The HAU model was used to quantify the demand response potential for the major household appliances. It is important to note that this study is not an optimisation study. It does not seek to match demand with the supply. The study is asking the question “to what extent can the demand profile be shaped by shifting the appliances to another time?” through an energy demand perspective (see Section 1.4 for the research question). It intends to provide insights into analysis and evidence of how much flexibility can be offered by the households by shifting their appliance use and identifying the evidence gaps in this area. The application of this model can quantify the demand flexibility to help provide insights to the following cases:

- Demand response can reduce the stress on network infrastructure by smoothing the demand
- Reduce the need for back-up gas plants by shifting demand away from the peak
- Help to match the supply profiles of low carbon resources by shifting demand when low carbon electricity is available
- Minimize electricity cost of a customer by shifting the flexible demand with respect to a varying price signal

The last two bullet points can be studied when supply generation profiles of low carbon resources such as wind power generation or photovoltaic generation are available, or time-based electricity prices on the utility level are available to see how much a household can save by shifting appliance use to cheaper time periods. This is not studied here. However, it is important to note that the HAU model is completely capable of doing this form of analyses if the supply data is available.

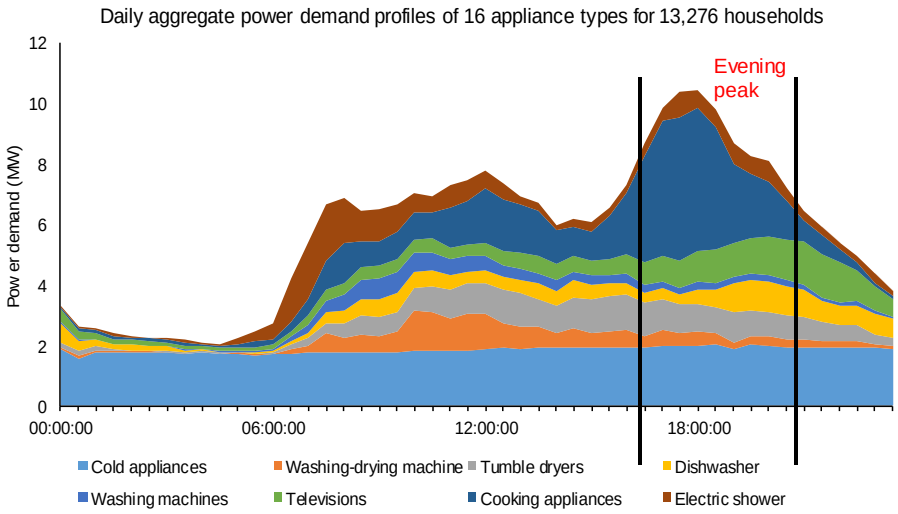
The application of the HAU model explored in Section 6.4 focuses on smoothing the power demand profile, shifting the demand from peak hours to lower power demand time slots. How much flexibility the households can offer will be tested with different appliance types. Similarly, the flexibility that can be offered from different household types can be compared.

A stochastic approach was taken to model demand response using the platform that HAU model provides. The method was used on the aggregated electricity demand profiles generated from 13,276 households. The method follows the steps below:

- The HAU model is applied to 13,276 households from the 2013-2014 EHS, which has been allocated with appliances by the appliance ownership model using linked variables to generate one-day household appliance electricity demand profiles (see Section 6.4.2).
- An appliance to be shifted and time-slot where the appliance to be shifted to is determined (e.g. washing machine which was switched-on between 17:00-20:30 to be randomly shifted to a time after 21:00). Example cases are proposed for the shifting of an appliance for a particular time slot (see Table 6.11). For example, demand shifting of the dishwashers, which operate in the evening peak, are shifted to lower power demand time slots after 21:00.
- A random number between 0 and 1 is generated and is compared against the percentage of the households willing to shift their appliances.
- The results of the aggregate electricity demand profiles of 13,276 households with and without demand response is scaled up to national level using the weighting factors calculated by the 2013-2014 EHS study.
- The net electricity demand changes between the unchanged electricity demand (no demand shifting) and demand response case are calculated for different appliances and household types for assessing the demand flexibility offered by different appliance types.

Figure 3.17 explains the method for modelling the demand response with an example case for shifting the usage of dishwashers.

Step 1: Generate a daily aggregate appliance electricity demand profile for 13,276 households.



Step 2: Focus on one time-slot and determine an appliance to shift.
E.g. Dishwashers from evening peak (17:00 to 20:30 pm)

Step 3: Pick the households which have switched-on their dishwashers in the chosen time-slots and stochastically determine whether these households will switch-on their dishwashers out of the chosen peak electricity load to lower energy demand depending on the probabilities defined by the cases. → Example: If randomly generated number is lower than the probability that the households agrees to shift the appliance to lower energy demand (for example, in cases such as 0.20, 0.40 etc.)

	Percentage of the households willing to shift the usage of their dishwasher
Case 1 (no change)	0%
Case 2	20%
Case 3	40%
Case 4	60%
Case 5	80%
Case 6 (every household shifts)	100%

Step 4: Scaled up the results of aggregate electricity demand profiles of 13,276 households with and without demand response to national level using the weighting factors calculated by the 2013-2014 EHS study.

Step 5: Analyse of the effect of shifting the usage of the appliances to the time slots with lower demand: net load changes and additional peaks.

Figure 3.17 Schematic of modelling the demand response using the HAU model.

3.8 CHAPTER 3: SUMMARY

The research design and methods used in this research to meet the aim and objectives and answer the research questions identified in Chapter 1 have been presented and described.

The datasets used in this research were from different sources (Section 3.3). The HES data acquisition was coordinated by DECC in the UK. The 2011 EFUS and 2013-2014 EHS datasets were both downloaded from the UK Data Archive. The datasets were used for different purposes. The 2011 HES dataset was used to model the HAU model and household electricity demand model. The 2011 EHS was used as the nationally representative sample of households to be modelled for the appliance electricity demand model. The 2011 EFUS dataset was used to develop the appliance ownership model.

This thesis identified three appliance behaviour metrics which are i) the number of switch-on events that occur over a specified time-period (e.g. a day or a month); ii) the time of day when the switch-on events occur; and iii) the duration of appliance use (the length of time that the appliance is switched on for) (Table 3.12).

This chapter has also outlined the stages of data processing and the methods of data analysis used in this research. Data cleaning was carried out on the 2-minute appliance power measurements prior to analysis (Section 3.3.3). Visual inspection of time series plots was used to identify incorrect readings. Comparing the expected and actual number of daily readings for each appliance was used to identify missing data. For wet appliances, appliance behaviour metrics is determined through visual data inspection and for rest of the appliances, an algorithm is configured to determine the metrics (Section 3.5.1). ANOVA (Analysis of Variance) was performed to test the significance of variation in the number of switch-on events, switch-on times and duration length of appliance usage across household types, occupant number, days of the week and seasons (Section 3.5.5).

In addition, the methods to develop the HAU model and appliance electricity demand model are explained (Section 3.5.3). The HAU model uses probability density functions for switch-on times and cumulative distribution functions for number of switch-on events per day and duration and power demand to implement a stochastic

modelling process. Two approaches were proposed where the PDF and CDF can be calculated either as a PDF and CDF for each household with a particular appliance type (i.e. 176 CDFs representing each household with washing machines in the HES dataset) or it can be the PDF and CDF based on an average household (i.e. one CDF based on averaging 176 households with washing machines in the HES dataset).

The methods for modelling the appliance ownership are presented (Section 3.5.5). A stochastic approach is taken when modelling the appliances in the households by randomly populating the “EHS household sample”. Three methods were proposed for modelling the appliance ownership which are i) assigning appliance sets, ii) assigning individual appliances independently and iii) assigning individual appliances dependently. The results and comparison of these methods are shown in Section 6.2.

Methods of modelling of demand response using the HAU model is explained in Section 3.7. A stochastic approach was taken to model demand response using the platform that HAU model provides. The method shifts the appliances in the peak times stochastically under different scenarios to a lower power demand and calculates the net electricity demand changes between demand response cases and without any demand shifting.

4 RESULT #1: APPLIANCE BEHAVIOUR MODELLING

4.1 INTRODUCTION

This chapter describes the calculation of the appliance behaviour metrics and the simulation results of the appliance behaviour modelling.

Section 4.2 presents the results of the calculation of the occupant and appliance behaviour metrics for appliance use chosen for this study which are i) number of switch-on events, ii) switch-on times of the day and iii) duration of the appliance use for 16 appliances. Section 4.3 presents the simulation results of the appliance behaviour model and compares the results with the measured data for 16 appliances for each appliance behaviour metric. It also presents the representation of the variation in the model results.

4.2 CALCULATING THE APPLIANCE BEHAVIOUR METRICS

4.2.1 Number of switch-on events

For each appliance in the HES dataset, the number of switch-on events (Metric 1) per day was calculated using the approach and definition given in Section 3.5.1 (Table 3.12). Table 4.1 shows the summary statistics for the results of number of switch-on events for the 225 homes in the HES dataset. For example, the average number of switch-on events per day for washing machines for a household is calculated as the total number of switch-on events during the monitoring period divided by the number of days monitored. Then, the mean of average number of switch-on events per day is calculated by dividing average number of switch-on events per day by the number of households.

For appliance categories, cold appliances have the highest average daily number of switch-on events, a mean of 28.5 switch-on times per day based on the 332 cold appliances in the dataset. Wet appliances have the lowest average daily number of switch-on events with a mean of 0.75. Chest freezers are the appliance type that have

Table 4.1.Statistics for average daily number of switch-on events for each appliance type as recorded in the 225 homes in the HES dataset

Appliances			Average daily number of switch-on events for each appliance type over the monitoring period[1]				
Appliance category	**Appliance Types**	**n**	**Mean[2]**	**95% C.I[3] of the mean**	**Minimum**	**Maximum**	**Median**
Wet appliances	Washing machine	176	0.78	±0.08	0.04	3.5	0.6
	Washing-drying machine	18	1.03	±0.46	0.10	3.8	0.8
	Tumble dryer	86	0.71	±0.13	0.04	3.4	0.6
	Dishwasher	84	0.65	±0.07	0.10	3.8	0.6
	All	364	0.75	±0.06	0.04	3.8	0.6
Cooking appliances	Cooker	105	2.09	±0.39	0.04	9.8	1.5
	Oven	44	0.98	±0.33	0.04	5.6	1.3
	Hob	9	1.35	±0.44	0.50	2.5	0.3
	Grill	5	0.24	±0.10	0.07	0.4	0.7
	All	163	1.74	±0.30	0.04	9.8	1.1
Televisions	TV1	86	2.20	±0.24	0.04	5.8	1.9
	TV2	44	1.56	±0.35	0.04	5.0	1.7
	TV3	21	0.94	±0.45	0.04	3.4	0.5
	All	151	1.84	±0.20	0.04	5.8	1.8
Electric shower		73	1.02	±0.16	0.04	1.5	1.0
Cold Appliances	Fridge	88	22.2	±3.50	2.80	85.4	17.6
	Fridge freezer	129	27.7	±3.30	2.90	125.3	24.0
	Chest freezer	34	42.6	±9.80	5.50	109.7	36.0
	Upright freezer	81	29.4	±3.50	4.40	95.9	25.9
	All	332	28.5	±2.13	2.80	125.3	36.5

[1]Average daily number of switch-on events is calculated as the average (mean) of the number of switch-on events for each day over the monitoring period. For example, if an appliance is monitored for 30 days, then the average daily number of switch-on events is the mean of 30 values, where the 30 values are the number of switch-on events that occur on each of the 30 days.
[2]This 'mean' refers to the mean of the average daily number of switch-on events for each appliance type. For example, in the case of washing machines this is calculated as the mean of 176 values, where each value is the average daily number of switch-on events for one washing machine. The other statistics in this table are calculated in a similar manner.
[3]This refers to the 95% confidence interval of the mean

the highest average daily number of switch-on events with a mean of 42.6 switch-on times per day based on the 34 chest freezers in the dataset. The results highlight the variation in average daily number of switch-on events for all appliance types. For example, the results show that one chest freezer has an average of 109.7 switch-on events per day throughout its monitoring period (the highest observed in the dataset for chest-freezers) and another had an average of 5.5 (the lowest observed). This is caused by the constant cycling of the chest freezers as the compressor switches on and off throughout the day. The results show that one chest freezer has an average of 109.7 switch-on events per day throughout its monitoring period (the highest observed in the dataset for chest freezers) and another had an average of 5.5 (the lowest observed). Similarly, one of the TV1 has an average of 5.8 switch-on events per day throughout its monitoring period (the highest observed in the dataset for

televisions) and another had an average of 0.04 (the lowest observed). Grills have the lowest number of daily switch-on times, a mean of 0.24 switch-on times per day based on the 5 grills in the dataset.

Number of switch-on events for different days, occupant numbers and household types

Figure 4.1 shows the mean of average number of switch-on events per day for each appliance type with their 95% confidence intervals of the 225 homes in the HES dataset plotted across different days of the week, different occupant numbers, household types. There is little variation of the mean of average daily number of switch-on events between the days of the week. It is difficult to comment on the variation among the number of occupants as the sample size is small or zero where the appliances are not present in all of the households, occupants and day groups. This includes several cooking appliances such as grills (n=5), hobs (n=9) and TV3 (n=21). To see whether the differences are significant, one-way ANOVA was performed. A one-way ANOVA test was conducted to compare the effect of household type, occupant number and day types on the mean of average number of switch-on events per day. Tables of p-value of Levene's test for hypothesis of equal variance and p-value of ANOVA test are given in more details in Appendix A. The ANOVA test results show that for dishwashers there is a significant effect of household type on the mean of average number of switch-on events per day at the $p<0.05$ [$F(2,86)=5.312$, $p=0.001$]. Similarly, there is a significant effect of occupant number on the mean of average number of switch-on events per day at the $p<0.05$ [$F(2,86)=6.091$, $p=0.000$]. For upright-freezers, the ANOVA test results show that there is a significant effect of occupant number on the average daily number of switch-on events at the $p<0.05$ [$F(2,86)=3.615$, $p=0.006$]. For remaining of the appliances, ANOVA results show that there is not a significant effect of household types, occupant numbers and day types on the average daily number of switch-on events. Therefore, for modelling the number of switch-on events, the dataset was not divided into different groups.

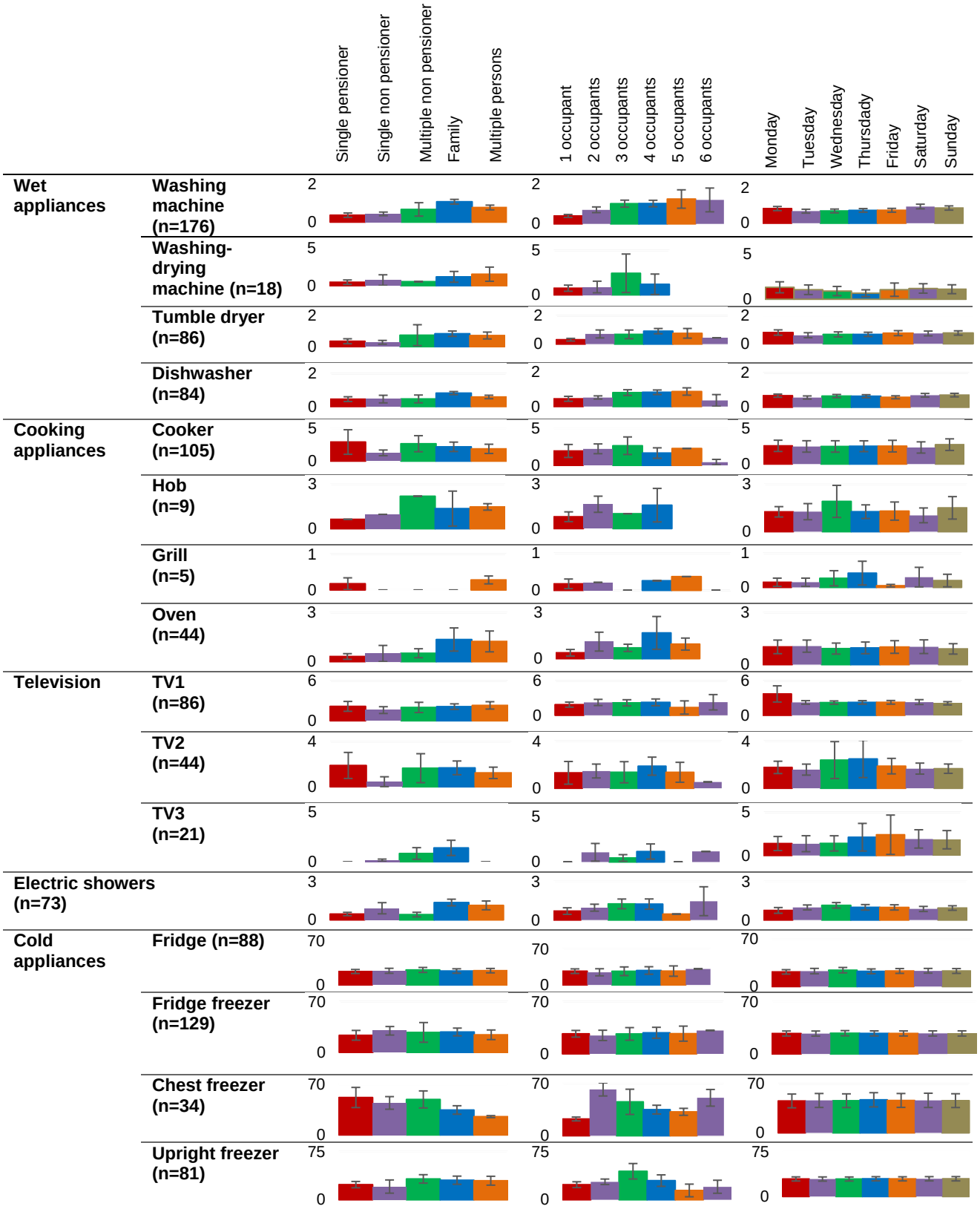


Figure 4.1 Mean number of switch-on events per day per appliance across different household types, occupant numbers and days of a week

Number of switch-on events across seasons

Figure 4.2 shows the mean of the average number of switch-on events per day with their 95% confidence intervals (error bar) for 16 appliances calculated for quarterly times (seasons); winter, spring, summer and autumn. Mean of average number of switch-on events per day were calculated as explained in Section 4.2.1 Both monthly monitored households and yearly monitored households were used to calculate the average number of switch-on events per day. TV3 is not shown in the graphs as monitoring period were missing in some of the seasons in the HES sample.

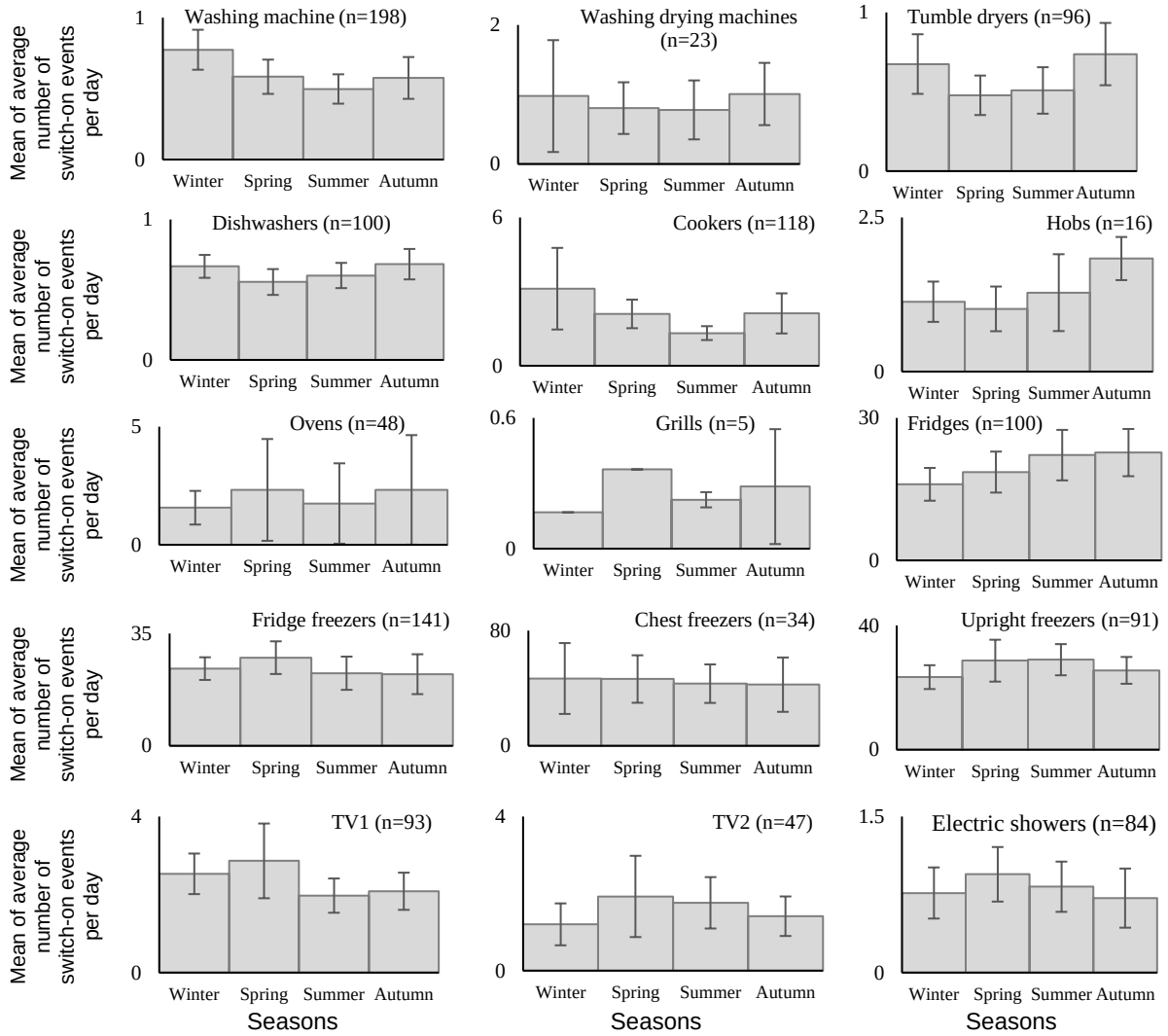


Figure 4.2 Mean of number of switch-on events per day per seasons for seasonality factor (monthly and yearly monitored households are used to calculate the mean of the switch-on times per day) (TV3 is not shown because monitoring of TV3 was not done in some of the months such summer and winter)

A one-way ANOVA test was conducted to compare the effect of season on the mean of average number of switch-on events per day. Tables of p-value of Levene's test for hypothesis of equal variance and p-value of ANOVA test are given in Appendix A. Only for washing machines, the ANOVA test results show that there is a significant effect of seasonality on the average daily number of switch-on events at the $p<0.05$ [$F(2,327)=2.983$, $p=0.031$]. For the rest of the appliances, the ANOVA test results show that there is a no significant effect of seasonality on the average daily number of switch-on events at the $p<0.05$. This shows that occupants habits do not depend on the season when cooking, watching TV or taking showers. The change of number of switch-on times of washing machines can be due to changes of clothes in different seasons. More clothes can be washed in one single cycle as the clothes get lighter which could lead to a lower number of switch-on events of washing machines.

Number of daily usages

The cumulative distribution functions of the number of switch-on events per day for the 16 appliance types are shown in Figure 4.3. These results are different from Table 4.1 in that the number of switch-on events per day is shown (which is Metric 1) for the 225 homes instead of average number of switch-on events per day per household. For example, CDF of washing machines consists of 3678 points taken from the switch-on events of 176 households, and the probability of number of switch-on events per day is shown for 0 to 11 times. The CDFs graphs are important to show the variation of number of switch-on within different days whereas the average number of switch-on cannot show this variation. The CDFs shown in Figure 4.3 are used for determining the switch-on events in Step 1 of Approach 2 (Section 3.4.4).

The results show the variation in daily number of switch-on events observed for all appliance types in the HES dataset with some days recording no use of appliance (0 switch-on events) and other days recording many switch-on events. For example, grills were not used at all for 80% of the days observed (highest observed) whereas all cold appliances had at least one number of switch-on events per day (lowest observed). The cold appliances have the highest number of switch-on events and one chest freezer had 144 number of switch-events in a single day. This is caused by the constant cycling as the compressor switches on and off throughout the day.

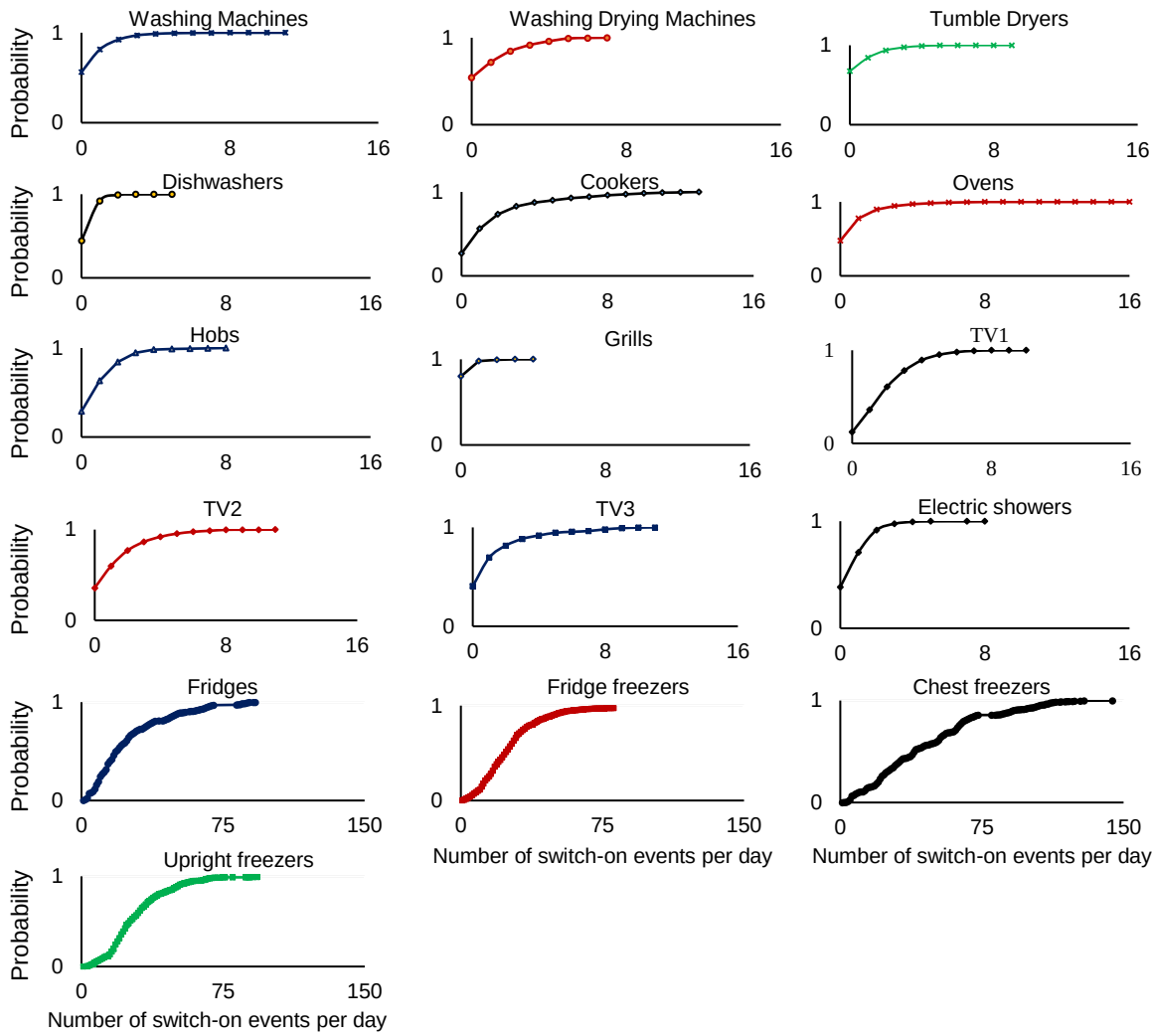


Figure 4.3 Cumulative distribution of daily number of usages of the 16 appliance types

4.2.2 Switch-on times daily profiles

Figure 4.4 shows the probability of mean hourly switch-on times varying over daily profiles for the 16 appliance types. These profiles were calculated using the definition given in Section 3.4.4 and shown here in hourly time slots to demonstrate the overall trend of the profiles. However, for the modelling, two minutely probabilities of switch-on times are used (the probability of 2-minute switch-on times varying over daily profiles are shown in Appendix B). Each point on the graph shows the probability of switch-on of an event over the time of the day. The results highlight the differences that occur in switch-on times across appliance categories and appliance types. Figure 4.4 shows that different appliances are used at different times of the day. Cooking appliances are switched-on around morning, noon and evening times which are presumably meal

times. Peak time occurs in the evening for dishwashers after the evening meal, whereas the peak time for washing machines is observed in the morning. Cold appliances switch-on repeatedly throughout the day. TVs are switched-on starting from the early morning and peak times occur both in the morning and in the evening.

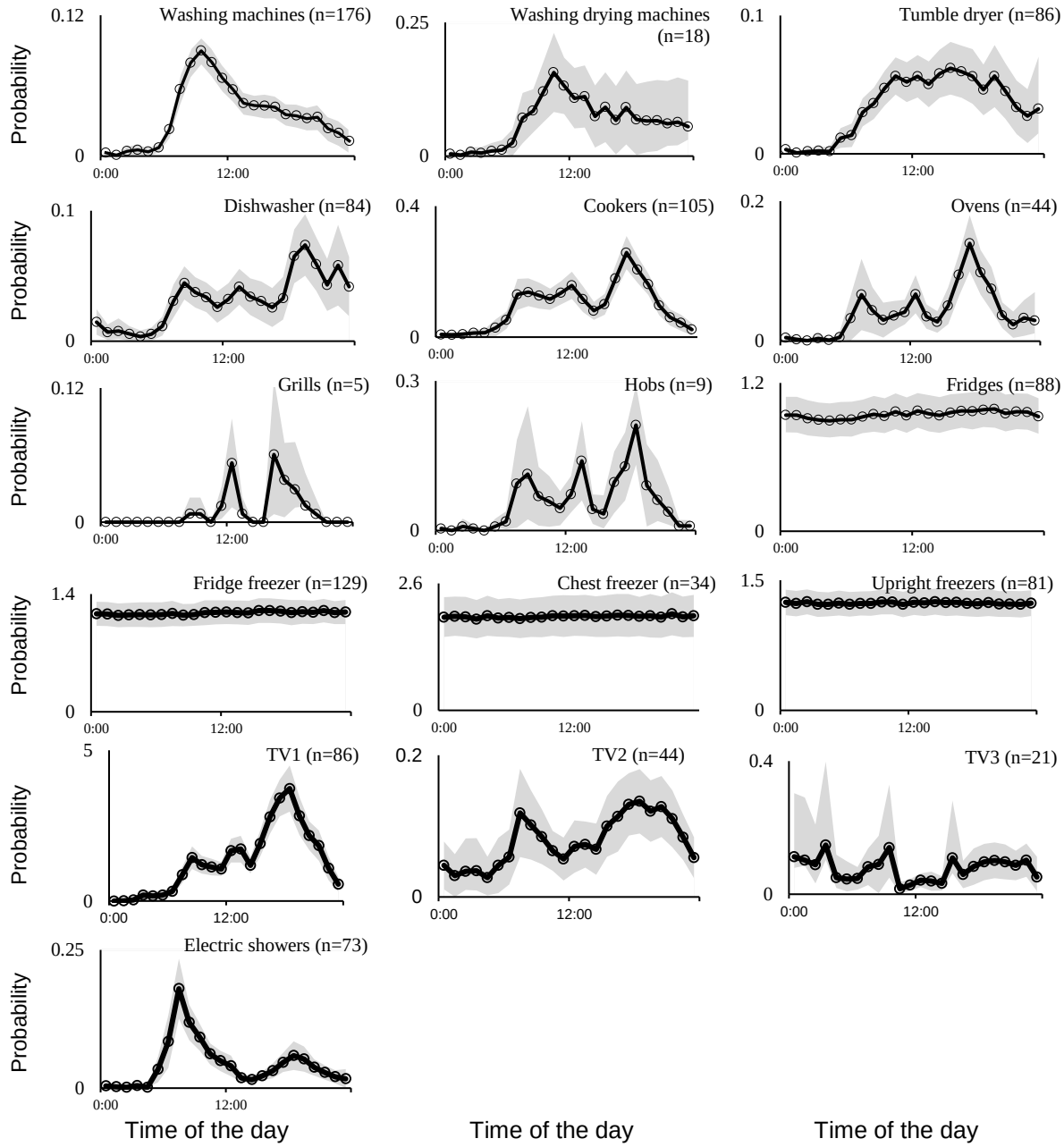


Figure 4.4. Probability of number of switch-on events (y-axis) vs. time of day (x-axis) for each appliance type as recorded in the 225 homes in the HES dataset. The mean of the average hourly number of switch-on times for each hour period is shown by the solid black line and white circle markers. The 95% confidence interval for the mean is shown by the shaded grey area. (24:00 is not shown here as it belongs to another day).

Switch-on time probabilities across different household types, occupant numbers and days of the week

The switch-on probabilities can be developed for different household types, occupant numbers and day types. However, data scarcity is an important factor which determines the number of groups. For example, if the data was divided into five household types according to Table 3.9 and weekdays/weekends, the number of data for each group is either very small or zero as explained in Section 4.2.1. Therefore, in this section three groups were constructed to test the difference between single person households (Type 1 and Type 2), multiple persons households (Type 3 and Type 4) and families (Type 5) for weekdays and weekends depending on the literature. These household type are groups due to the explained data scarcity issues, and are grouped depending on the 2013-2014 EHS. Table 4.2 summarises the number of homes used to construct the probabilities of switch-on times per day.

Table 4.2 Number of the homes used to construct the probability profiles of the switch-on times

Appliances		Number of homes monitored which are..		
Appliance category	**Appliance Types**	**Single person (Type1 and Type 2)**	**Multiple persons with no dependent children (Type3 and Type 5)**	**Family (multiple people with dependent children (Type 4)**
Wet appliances	**Washing machine**	45	82	49
	Washing-drying machine	6	6	6
	Tumble dryer	13	44	29
	Dishwasher	12	40	32
Cooking appliances	**Cooker**	26	47	32
	Oven	13	18	13
	Hob	2	4	3
	Grill	2	-	3
Televisions	**TV1**	26	38	22
	TV2	6	24	14
	TV3	-	13	8
Electric shower		19	36	18
Cold Appliances	**Fridge**	22	36	30
	Fridge freezer	38	58	33
	Chest freezer	8	14	12
	Upright freezer	12	41	28

Figure 4.5 shows the probability of mean hourly switch-on times varying over daily profiles for different household types and days of the week. These profiles are calculated using the definition given in Section 3.4.4 and shown here for hourly time slots to demonstrate the overall trend of the profiles. The objective of making these graphs is to compare; firstly, probability of mean hourly switch-on times varying over weekday and weekends for each household group; secondly, probability of mean hourly switch-on times of household groups are compared for weekdays and weekends. Examples from each appliance category namely; washing machines, cookers, TV1, electric shower and fridge are given.

Figure 4.5 shows that the shape of the profile does not differ greatly between household types. In other words, the peak time of the number of switch-on events of the appliances shown in Figure 4.5 occurs at similar times for different household types. For example, the peak time of the number of switch-on events of washing machines is in the morning between 9am to 11am for single person households. Similarly, the peak time of the switching-on the washing machines does not change with the household type which is again between 9am to 11am for multiple persons and families. Figure 4.5 also shows that the shape of the profile is similar between weekdays and weekends. The peak times of the appliance usage are in similar time-slots. For example, the switch-on probabilities of TV2 is randomly distributed and profiles between weekday and weekend are not distinctively different from each other. Cold appliances are switched-on throughout the day regardless of household type and day of the week. The results of other appliance types which are not presented here show similar trends to those shown here.

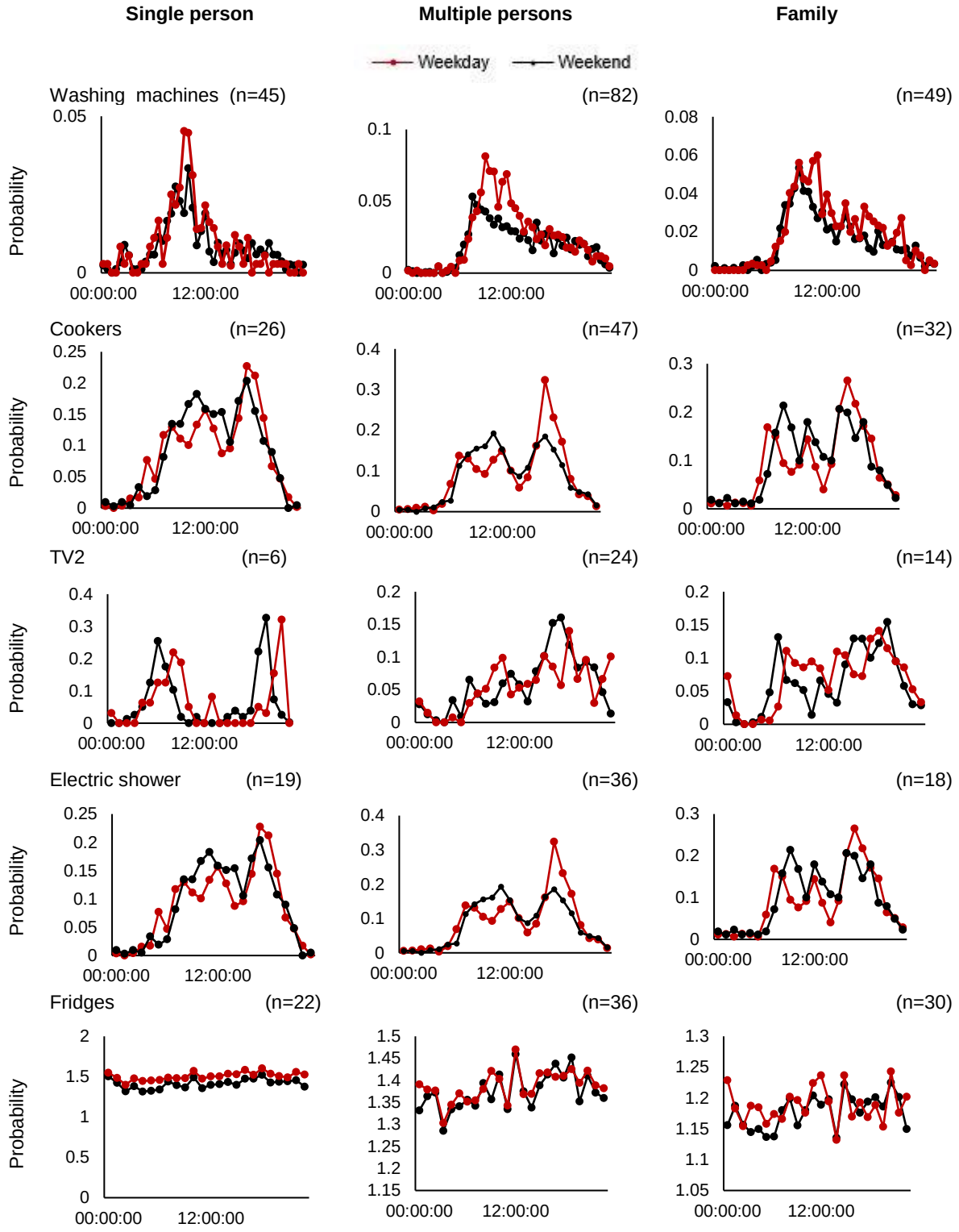


Figure 4.5 Comparison of weekday and weekend daily probability profiles of switch-on times of washing machines, cookers, TV2, electric showers and fridges of an average day for households with single person, multiple persons with no dependent children and family with dependent children. (again 24:00 is not indicated here as it belongs to the next day,last point for one day is 23:58).

4.2.3 Duration (run time of appliances)

For each appliance in the HES dataset, duration length of appliance use (Metric 3) per usage is calculated using the approach given in Section 3.4.3. Table 4.3 shows the summary statistics for duration length per usage for the 225 homes in the HES dataset. For example, the average duration length per usage for washing machines for a household is calculated by taking the average of the duration length per usage (75 minutes for the 1st cycle, 60 minutes for the 2nd cycle, 30 minutes for the 3rd cycle: the average is (75+60+30)/3=55 minutes of average duration length per usage for household 1). Then, the mean of average number of switch-on events per day is calculated by dividing average number of switch-on events per day by the number of households.

Table 4.3.Statistics for average duration per usage monitoring period (minutes) for each appliance over the monitoring period

Appliances		Average duration per usage for each appliance over the monitoring period (minutes)					
Appliance Category	**Appliance types**	**n**	**Mean**	**95% C.I of the mean (95%)**	**Min**	**Max**	**Median**
Wet appliances	**Washing machine**	176	75.7	±3.4	27.7	172.4	72.6
	Washing-drying machine	18	86.8	±28.0	53.0	211.6	73.0
	Tumble dryer	86	70.4	±12.8	21.0	165.2	65.0
	Dishwasher	84	79.2	±13.4	28.1	136.5	80.5
	All	364	75.8	±2.70	21.0	211.6	73.8
Cooking appliances	**Cooker**	105	40.7	±8.00	6.4	128.5	34.4
	Oven	44	47.0	±24.0	14.0	134.0	44.5
	Hob	9	37.5	±37.1	13.5	102.2	29.1
	Grill	5	11.9	±5.0	9.2	13.4	12.3
	All	163	39.6	±3.97	6.4	134.0	36.0
Televisions	**TV1**	86	160.2	±35.0	7.9	654.7	100.0
	TV2	44	119.7	±23.3	4.0	444.8	82.6
	TV3	21	129.8	±29.6	38.3	465.8	123.8
	All	151	134.4	±18.8	4.0	654.7	98.7
Electric showers		73	9.44	±0.95	2.0	25.5	8.7
Cold appliances	**Fridge**	88	36.6	±34.0	3.6	744.7	18.4
	Fridge freezer	129	38.4	±38.0	8.0	473.7	23.4
	Chest freezer	34	29.3	±28.9	5.5	206.1	14.7
	Upright freezer	81	27.8	±26.8	8.7	171.5	22.7
	All	332	36.6	±6.4	3.6	744.7	22.1

TV1 has the longest duration per usage, a mean of 160.2 minutes based on the 86 TV1 appliances in the dataset. The next longest are TV3 (129.8 minutes) and TV2 (119.7 minutes). Electric showers have the shortest duration per usage, a mean of

9.44 minutes based on the 73 electric showers in the dataset. After televisions, wet appliances are the appliance category with the second highest duration length of appliance use, a mean of 75.8 minutes of average duration length per usage in total based on the 364 wet appliances in the dataset. The results show that one electric shower has an average of 25.5 minutes of duration length of appliance use per usage throughout its monitoring period (the highest observed in the dataset for electric showers) and another had an average of 2.0 minutes (the lowest observed).

Durations for different days, occupant numbers and household types

Figure 4.6 shows the mean duration (minutes) of events for each appliance type with their 95% confidence intervals of the 225 homes in the HES dataset plotted across different days of the week, different occupant numbers, household types. The figures suggest that there is minimal variation among the household types, nor occupant numbers or the day of the week. It is difficult to comment on the variation among the number of occupants as the sample size is small or zero. This includes several cooking appliances such as grills (n=5), hobs (n=9) and TV3 (n=21).

A one-way ANOVA test was conducted to compare the effect of household type, occupant number and day types on the mean of average daily number of switch-on events. Tables of p-value of Levene's test for hypothesis of equal variance and p-value of ANOVA test are given in more details in Appendix A. ANOVA results show that there is not a significant effect of household types, occupant numbers and day types on the average duration length (minutes) of appliance usage. Therefore, when modelling duration, there is no need to categorise the distribution of durations for different subgroups.

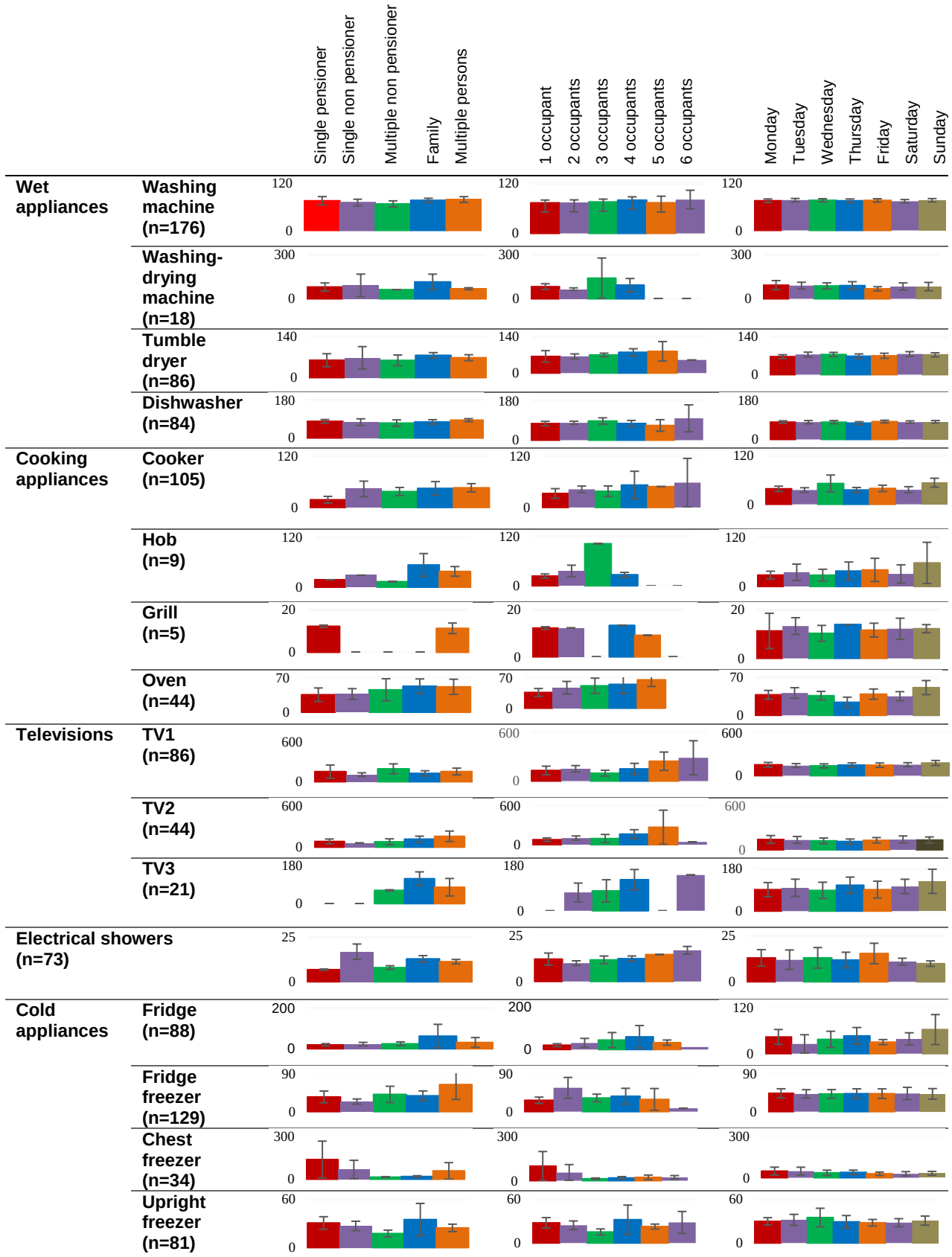


Figure 4.6 Mean of average duration length per usage across different household types, occupant numbers and day of the week

Durations for different hour slots

Figure 4.7 shows the mean of the durations (lengths) of appliance use with the 95% confidence interval that are started in the time interval of hourly slots (on the x-axis). For example, switch-on event of a cooker at 14:35 and 14:10 from all 105 households were grouped under 14:00. Then, the mean of each duration was calculated for different hourly time slots. To see whether the differences are significant, one-way ANOVA is performed. The ANOVA test results show that the null hypothesis of equal variances is rejected (Appendix A). It is concluded that there is a difference between the mean of the duration (minutes) between time-slots for all the televisions (TV1, TV2 and TV3) and cooking appliances (hob, grill, cooker and oven). Both televisions and cooking appliances are used longer in the afternoon and evening compared to mornings and nights. This could have an effect on the model performance which is discussed in Section 5.3.2. For wet appliances, cold appliances and electric showers, there is not significant difference between the mean of durations (minutes) between time-slots.

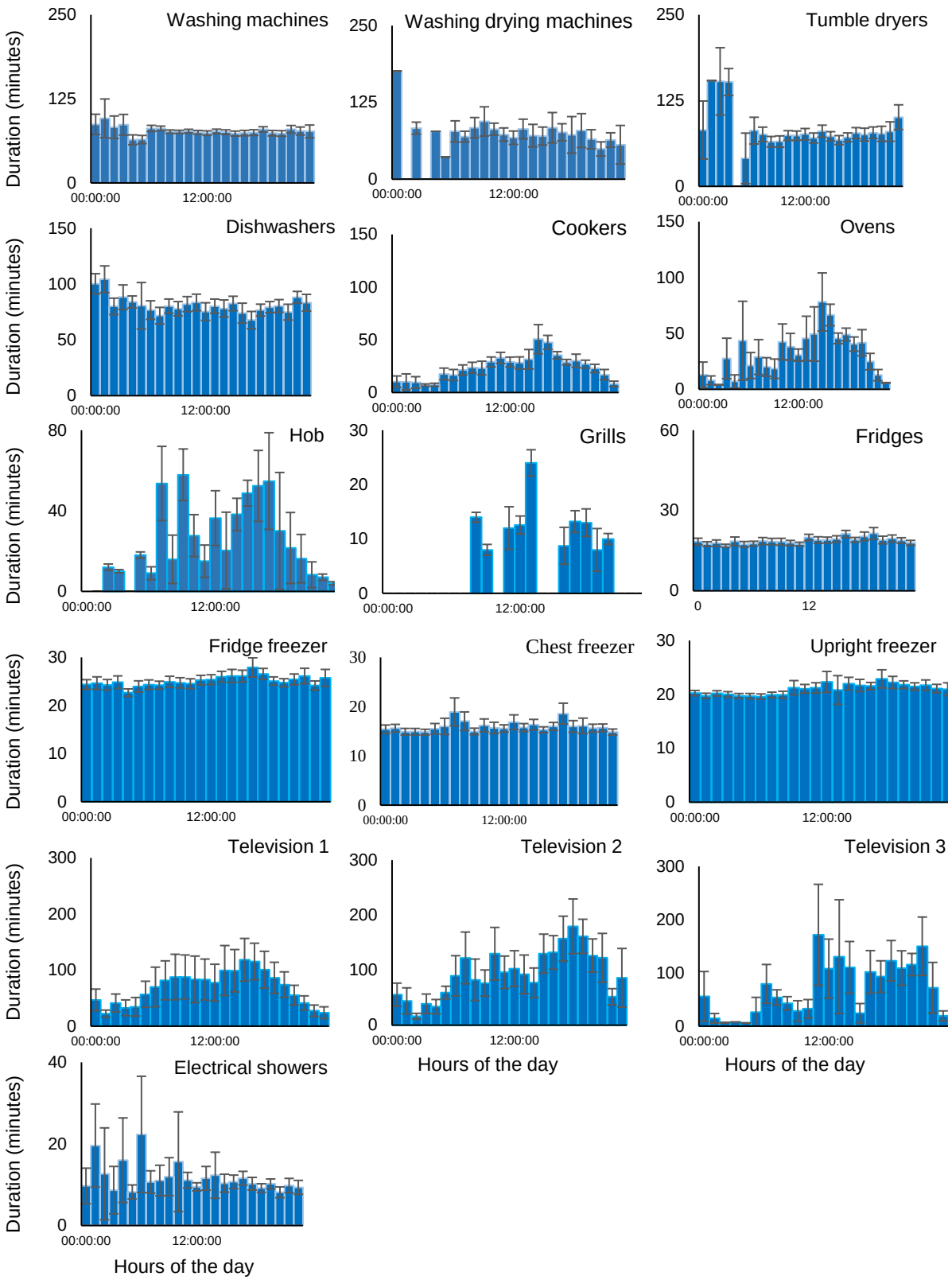


Figure 4.7 Mean of the durations of activities/appliance with the 95% confidence interval that are started in the time interval (on the x-axis)

Duration of each usage

The cumulative distribution functions of the duration length per usage in minutes for 16 appliance types are shown in Figure 4.8. These results are different from Table 4.3 in that the duration length for a usage is shown which is Metric 3 for the 225 homes instead of average duration length per usage per household. For example, CDF of washing machines consists of 3678 points taken from the washing machines cycles of 176 households, and the probability of duration length is shown for 2 to 240 minutes. The CDFs graphs are important to show the variation of duration length within different usage within the same household whereas the average duration cannot show this variation. The CDFs shown in Figure 4.8 are used for determining the duration in Step 3 of Approach 1 and Approach 2 (Section 3.5.3).

The graphs show that there is a great variation in the duration lengths of individual appliance usages in the HES dataset. Electric showers have low duration lengths, ranging between 2 to 50 minutes. One TV1 was switched-on for 1,350 minutes (almost a day) in a single day (the highest observed in the dataset for televisions). The variation in duration is high for cold appliances and the compressors appear to be on for a long time, in one case, for 2,090 minutes. Duration length per usage of wet appliances are less than 300 minutes with 80% of the durations were less than 100 minutes. The duration length of washing machines varied from 10 minutes to 244 minutes.

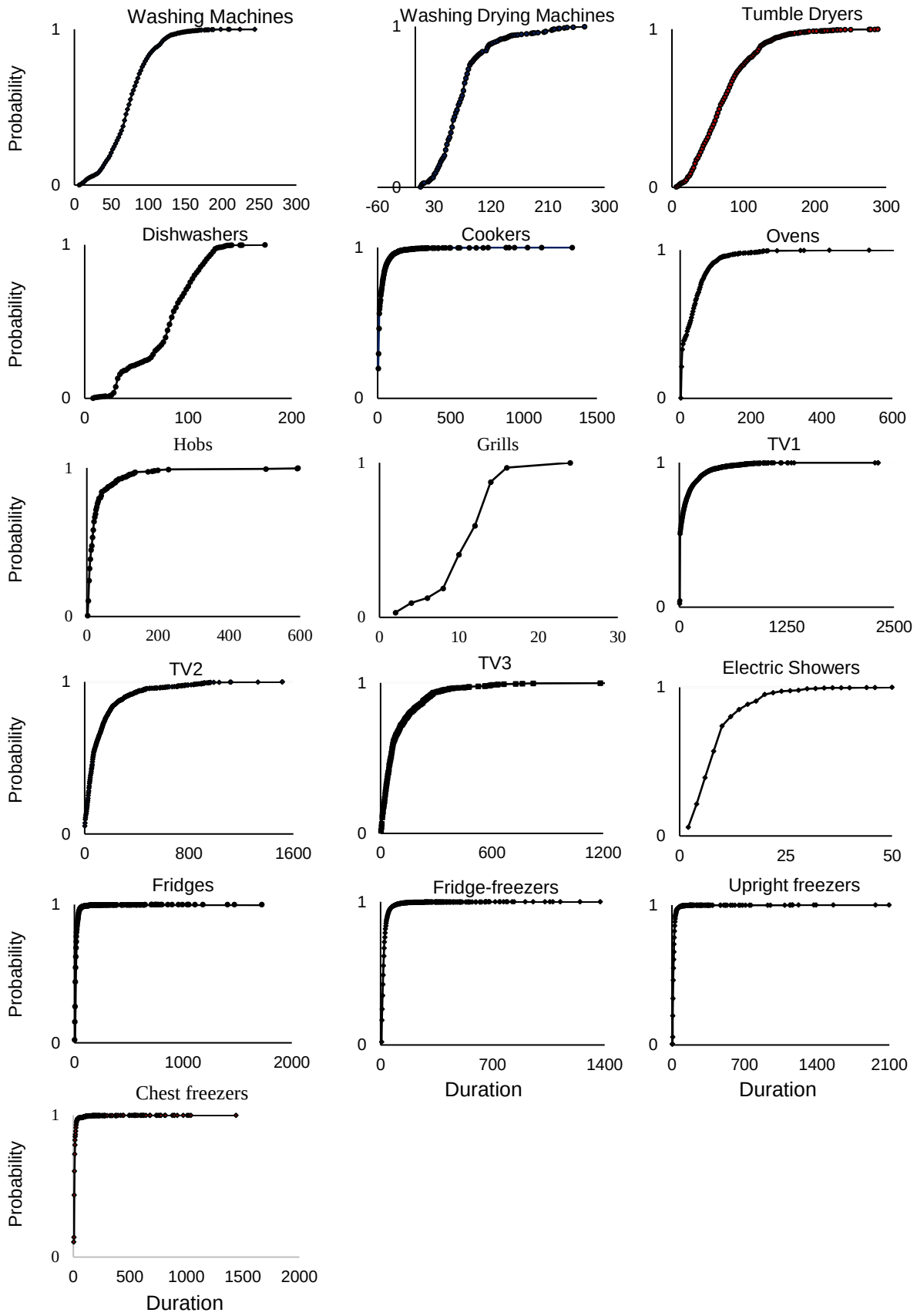


Figure 4.8 Cumulative distribution of duration length per usage of appliance for 16 appliances

4.3 SIMULATION RESULTS

The ability of the HAU model to recreate patterns similar to those observed in the monitored dataset is assessed in this section. Therefore, the monitored data is not divided into training and test sets in order to prevent the bias when comparing the approaches in the first part of the simulations. The modelling approaches are compared by their ability to replicate the following properties for each appliance types:

- Average daily number of switch-on events and variation of daily number of switch-on events

- Probability of the appliance being switched on for each time step of a day

- Duration at each use of the appliance

There is no sub population for household types nor day types are considered as the ANOVA results show that there is not a significant effect of household types, occupant numbers and day types on the appliance behaviour metrics. Profiles of households with 16 appliances are simulated using the methods explained in Section 3.5.3. The simulation results shown in this section have been generated by taking the average values of 100 simulation runs.

4.3.1 Comparison of the number switch-on events

First the results of the simulations for washing machines are presented as an example. Simulations are run for four model variants: Approach1_AvgHs, Approach1_IndHs, Approach2_AvgHs and Approach2_IndHs using the approach set out in Section 3.5.3. Here the average appliance PDF (AvgApp) is used to calculate appliance durations as this section is focussing on the Approach1/Approach2 and AvgHs/IndHs comparisons. Choosing AvgApp or IndApp has no effect on the number of switch-on events. The modelling approach (Approach 2) that first assigns the daily number of switch-on events, and then determines the time of the switch-on events by ‘stepping through’ the PDF and durations from CDFs whereas Approach 1 (similar to previous studies) does not first assign the daily number of events and simply determines the number of switch-

on events and switch-on times by 'stepping through' the PDF and durations from CDFs.

Each model variant is simulated 100 times and Figure 4.9 shows the distribution of the 100 simulation results for each of the model variants. One simulation shows the mean of average number of switch-on events of a washing machine per day of 176 washing machines simulated for a month. Box plot is formed of these 100 simulations results whereas measured value is only one taken from Table 4.1. It is clear that, on average, Approach1 underestimates the number of switch-on events per day compared to the measured data for all appliances. For example, Approach 1 predicts, on average 0.73 switch-on events per day for an average household PDF and 0.70 for an individual household PDF. Approach 2 predicts the number of switch-on events close to the measured data result, with both the average and individual household PDF results as 0.78. This is an important result as Approach 1 is the approach taken by many past studies (Paatero and Lund, 2006; Richardson et al.,2010) and the reasons why Approach 1 is under predicting is discussed in Section 7.2. Approach 2 improved the modelling of the number of switch-on events by assigning number of switch-on events for each day.

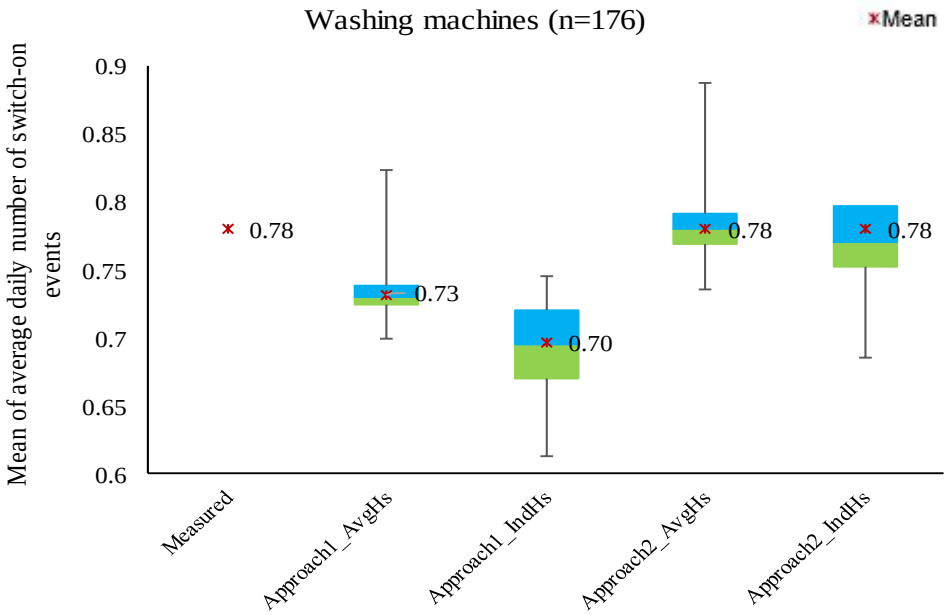


Figure 4.9 Boxplots of the mean of average daily number of switch-on events of washing machines resulting from 100 simulation runs. Approach1 uses a single-day PDF (Step 2) and Approach 2 uses a cfd (Step 1) to estimate switch-on events per day. AvgHS is an 'average household' and IndHs is an 'individual household'.

rather than average household results in greater variation in distribution of the simulation runs. This increased variation occurs because, for each of the 100 simulation runs, the same CDF is used for the AvgHs results whereas many different possible combinations of CDFs are used for the IndHs results.

Table 4.4 shows that the results seen in Figure 4.9 for washing machines are observed for all appliance types in the dataset. In Table 4.6 the measured, Approach1_AvgHs, Appraoch1_IndHs, Approach2_AvgHs and Approach2_IndHs results are shown for the mean average daily number of switch-on events, based on 100 simulation runs for each appliance type. The percentage difference of the mean value of simulation from the measured dataset is indicated in parenthesis. As can be seen from Table 4.4; the mean is underestimated by Approach 1 regardless of the HAU model variant. However, IndHs predicted the average daily number of switch-on events even significantly less than AvgHs in Approach 1 (up to -16%) for all appliances. Approach 2 predicted the average daily number of switch-on events much closer to the measured data for all appliances regardless its model variants.

Table 4.4.Statistics of the average number of switch-on events per day for 16 appliances of averaged from 100 simulation runs of Approach 1 and Approach 2 with model variants AvgHs_AvgApp and IndHs_AvgApp and measured value

			Mean of average daily number of switch-on events for each appliance type[1]				
Appliance category	**Appliance Types**	**n**	**Mea-sured**	**Approach 1**		**Approach 2**	
				AvgHs	**IndHs**	**AvgHs**	**IndHs**
Wet appliances	Washing machine	176	0.78	0.73 (-6%)	0.70 (-11%)	0.78 (0%)	0.78 (0%)
	Washing-drying machine	18	1.03	0.96 (-8%)	0.89 (-15%)	1.03 (0%)	1.03 (0%)
	Tumble dryer	86	0.71	0.67 (-5%)	0.64 (-9%)	0.71 (0%)	0.71 (0%)
	Dishwasher	84	0.65	0.62 (-5%)	0.59 (-9%)	0.65 (0%)	0.65 (0%)
	All	364	0.75	0.71(-5%)	0.68 (-10%)	0.75(0%)	0.75(0%)
Cooking appliances	Cooker	105	2.09	2.03 (-5%)	1.83 (-9%)	2.09 (0%)	2.09 (0%)
	Oven	44	0.98	0.95 (-5%)	0.87 (-9%)	0.98 (0%)	0.98 (0%)
	Hob	9	1.35	1.28 (-5%)	1.26 (-7%)	1.35 (0%)	1.35 (0%)
	Grill	5	0.24	0.24 (-4%)	0.23 (-1%)	0.24 (0%)	0.24 (0%)
	All	163	1.74	1.65(-5%)	1.62(-8%)	1.74(0%)	1.74(0%)
Televisions	TV1	86	2.20	2.07 (-6%)	1.99 (-9%)	2.20 (0%)	2.20 (0%)
	TV2	44	1.56	1.34 (-14%)	1.23 (-21%)	1.56 (0%)	1.56 (0%)
	TV3	21	0.94	0.87 (-7%)	0.81 (-14%)	0.94 (0%)	0.94 (0%)
	All	151	1.84	1.64(-11%)	1.51(-18%)	1.84(0%)	1.84(0%)
Electric shower		73	1.02	1.00 (-2%)	0.95 (-7%)	1.02 (0%)	1.02 (0%)
Cold appliances	Fridge	88	22.2	19.02 (-4%)	17.74 (-20%)	22.2 (0%)	22.2 (0%)
	Fridge freezer	129	27.7	23.30 (-16%)	21.81 (-21%)	27.7 (0%)	27.7 (0%)
	Chest freezer	34	42.6	36.11 (-15%)	33.01 (-23%)	42.6 (0%)	42.6 (0%)
	Upright freezer	81	29.4	25.18 (-14%)	23.02 (-22%)	29.4 (0%)	29.4 (0%)
	All	332	28.5	24.23(-15%)	22.23(-22%)	28.5(0%)	28.5(0%)

[1] The percentage difference of the mean value of simulation from the measured value

It is also important to test that the simulation process predicts a reasonable variation in the switch-on events of the appliances across households. Figure 4.10 shows the distribution (boxplots) of the values of average number of switch-on events per day of washing machines resulting from one simulation run (176 washing machines simulated once) with the measured values. Distribution of measured values shows the values of average number of switch-on events per day of 176 washing machines values and the mean of the 176 washing machines is 0.78. The HAU variants' ability to capture the variability of the average daily number of switch-on events is tested depending on how the switch-on PDFs are developed (AvgHs vs. IndHs). Results show that IndHs_AvgApp is better at capturing the variation of daily average number of switch-on events as opposed to AvgHs_AvgApp. The interquartile range (the difference between the 25th quantile and 75th quantile) is calculated for each HAU model variant to indicate the variability around the median; the interquartile range is reduced from 0.64 to 0.25 by 61% for AvgHs_AvgApp whereas for IndHs_AvgApp it is increased from 0.64 to 0.75 by 18%. The range of mean of average daily number of switch-on times (difference between maximum and the minimum value) is reduced from 3.48 to 0.86 (by 75%) and from to 3.48 to 3.42 (by 2%) for AvgHs_AvgApp and IndHs_AvgApp, respectively.

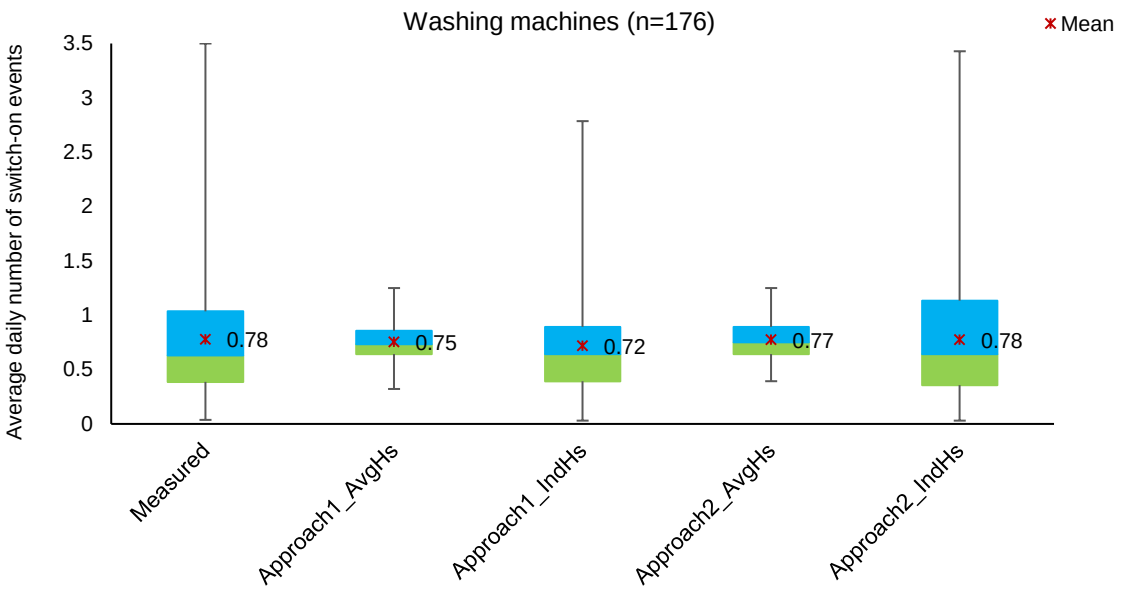


Figure 4.10.Boxplots of the average daily number of switch-on events of washing machines resulting from one simulation compared with the measured average daily number of switch-on events (176 washing machines)

4.3.2 Comparison of switch-on times profiles

Half-hourly (30 minutes) mean of daily probability of switch-on times of the 100 simulations of the HAU model are compared with measured daily probability of switch-on times for 16 appliance types in Figure 4.11 to Figure 4.14. All model variants of the two main approaches of the HAU model do comparatively well in predicting the half hourly probability switch-on times over time of the day. However, as Approach 1 predicts the mean of the number of switch-on events less (Table 4.4), there is a gap between the lines although the shape of the daily profile (the time of the peak values etc.) is predicted well.

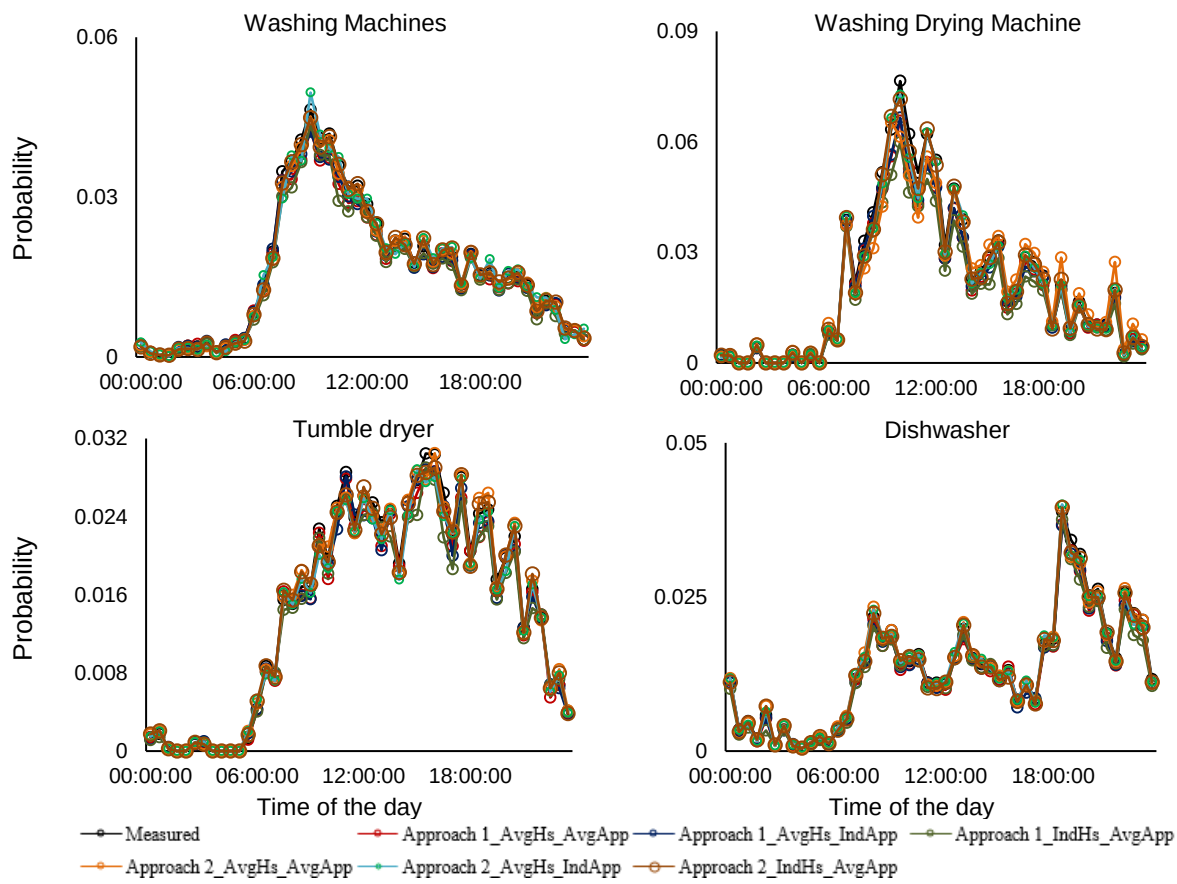


Figure 4.11 Comparison of the half hourly (30 minutes) probability of switching on of measured and 100 simulated households of wet appliances for a day

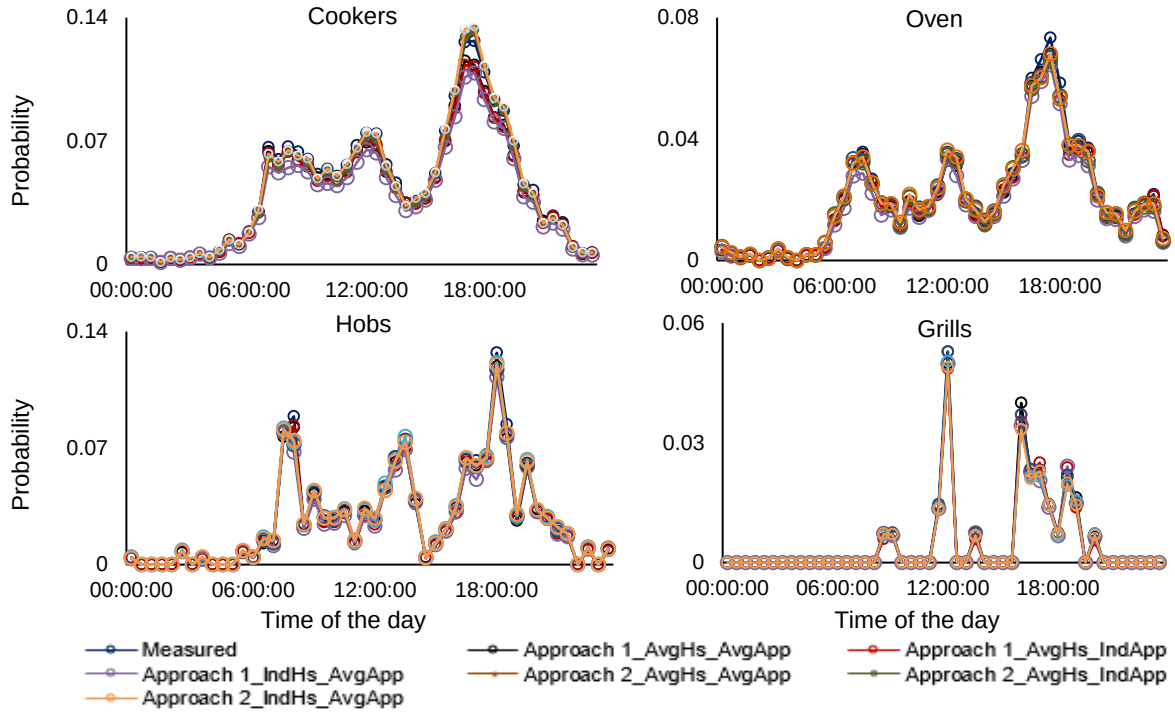


Figure 4.12 Comparison of the half hourly (30 minutes) probability of switching on of measured and 100 simulated households of cooking appliances

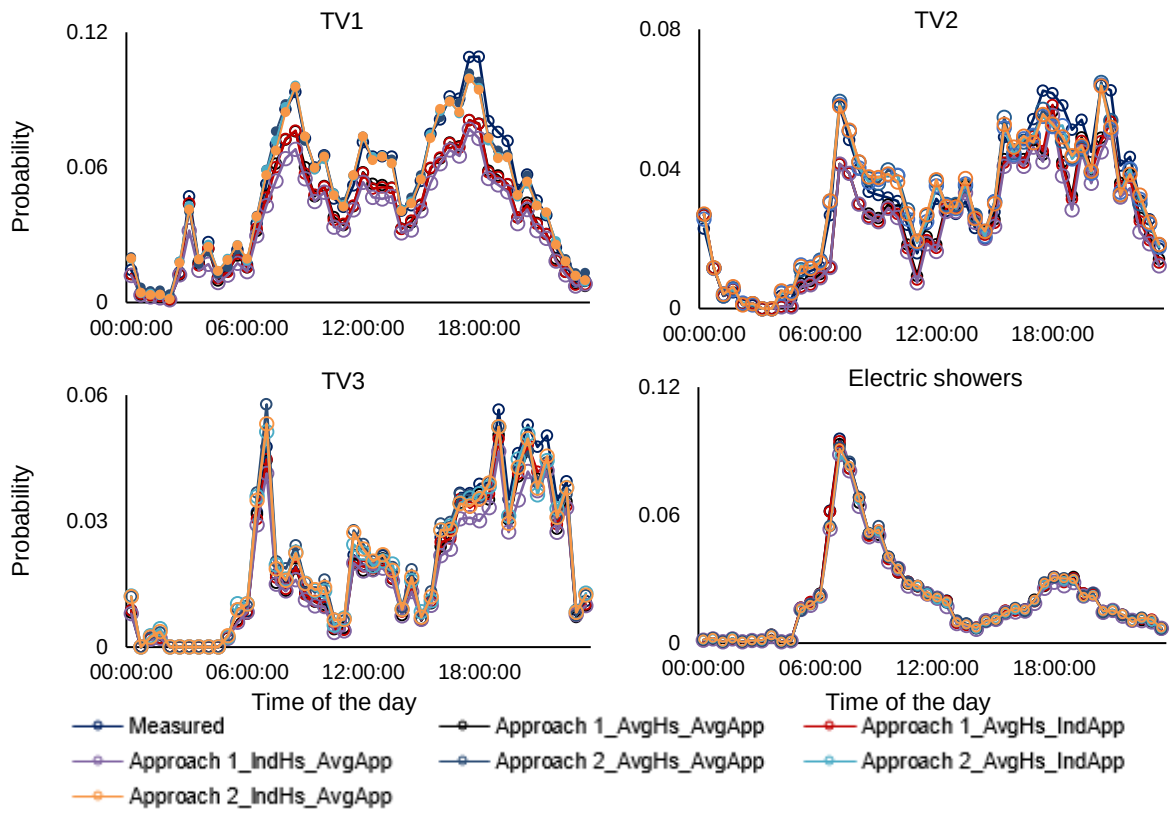


Figure 4.13 Comparison of the half hourly (30 minutes) probability of switching on of measured and 100 simulated households of televisions and electric showers

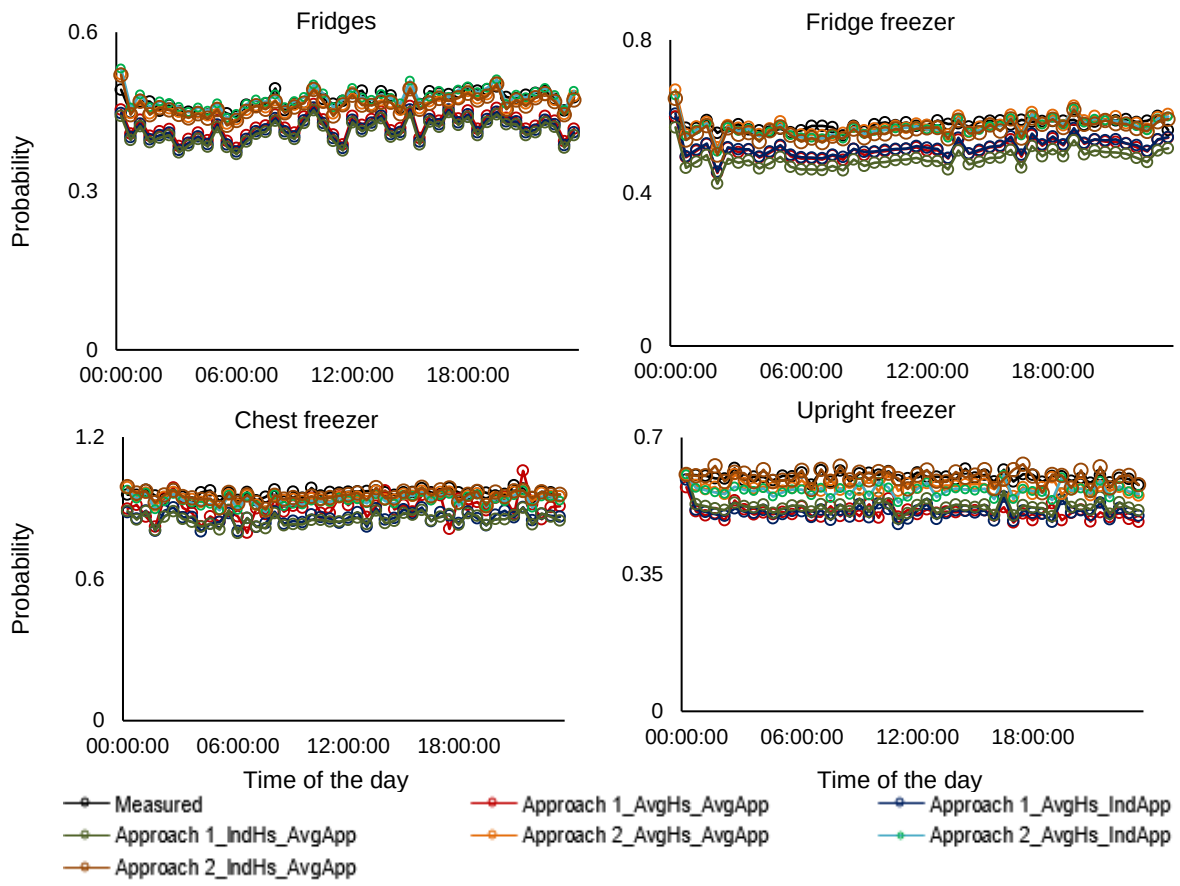


Figure 4.14 Comparison of the half hourly (30 minutes) probability of switching on of measured and 100 simulated households of cold appliances

4.3.3 Comparison of duration distributions

The results of the simulations for average duration length per usage for each appliance type are presented in Table 4.5. Simulations are run for four model variants: Approach1_AvgHs, Approach1_IndHs, Approach2_AvgHs and Approach2_IndHs (as defined in Section 3.5.3). Each model variant is simulated 100 times. As expected, since both approaches use the same method (using step 3) to predict the duration for each usage, there was not a difference in the values of average duration length per usage for each appliance over the monitoring period among Approach 1 and Approach 2 regardless of the model variant. Both modelling approaches predicted the average duration length per usage correctly.

Table 4.5. Comparison of the mean of the duration length (minutes) of appliance usage for 16 appliances of the 100 simulations of model variants AvgHs_AvgApp and IndHs_AvgApp

				Average duration length per usage for each appliance type			
Appliance category	**Appliance Types**	**n**	**Measu-red**	**Approach 1**		**Approach 2**	
				AvgApp	**IndApp**	**AvgApp**	**IndApp**
Wet appliances	Washing machine	176	75.7	76.7 (1%)	76.4 (0%)	75.6 (0%)	75.73 (0%)
	Washing-drying machine	18	86.8	86.9 (0%)	85.5 (-1%)	86.7(0%)	86.83(0%)
	Tumble dryer	86	70.4	71.8 (2%)	70.2 (0%)	70.3(0%)	70.2(0%)
	Dishwasher	84	79.2	81.1 (2%)	81.0 (2%)	79.1(0%)	79.23(0%)
	All	364	75.8	77.3(0%)	75.3(0%)	75.8(0%)	75.8(0%)
Cooking appliances	Cooker	105	40.7	39.5 (-3%)	40.3 (1%)	40.68(0%)	40.59(0%)
	Oven	44	47.0	46.1 (2%)	46.5 (0%)	46.9(0%)	46.81(0%)
	Hob	9	37.5	36.8 (-2%)	37.4 (0%)	37.5(0%)	37.39(0%)
	Grill	5	11.9	11.6 (0%)	12.0 (1%)	11.9(0%)	11.79(0%)
	All	163	39.6	39.2(-1%)	39.3(0%)	39.6(0%)	39.3(0%)
Televisions	TV1	86	160.2	161.9(1%)	161.3 (1%)	160.3(0%)	160.18(0%)
	TV2	44	119.7	120.1(0%)	120.0 (0%)	119.8(0%)	119.68(0%)
	TV3	21	129.8	130.8(1%)	129.2 (0%)	129.9(0%)	129.78(0%)
	All	151	134.4	134.6(1%)	134.4(0%)	134.4(0%)	134.5(0%)
Electric shower		73	9.4	9.4 (0%)	9.4 (0%)	9.3(-1%)	9.4 (0%)
Cold appliances	Fridge	88	36.6	36.6 (0%)	36.6(0%)	36.6 (0%)	36.6(0%)
	Fridge freezer	129	38.4	38.7(0%)	38.4(0%)	38.7(0%)	38.4(0%)
	Chest freezer	34	29.3	29.7(0%)	29.3(0%)	29.7(0%)	29.3(0%)
	Upright freezer	81	27.8	27.7(0%)	27.8(0%)	27.7(0%)	27.8(0%)
	All	332	36.6	36.8(0%)	36.5(0%)	36.6(0%)	36.6(0%)

It is also important to test that the simulation process predicts a reasonable variation in the duration length per usage of the appliances across households. Figure 4.15 shows the distribution (boxplots) of the values of duration length for each usage of washing machines resulting from one simulation run (176 washing machines simulated once) of AvgHs_AvgApp and AvgHs_IndApp of Approach 2 with the measured values. Distribution of measured shows the values of average number of switch-on events per day of 176 washing machines values and the mean of the 176 washing machines is 75.7. Results show that AvgHs_IndApp is better at capturing the variation of daily average number of switch-on events as opposed to AvgHs_AvgApp. The interquartile range (the difference between the 25th quantile and 75th quantile) is calculated for each HAU model variant to indicate the variability around the median; the interquartile range is reduced from 30.8 to 9.6 by 69% for AvgHs_AvgApp whereas for AvgHs_IndApp it is increased from 30.8 to 35.7 by 16%. The range of mean of average daily number of switch-on times (difference between maximum and the minimum value) is reduced from 144.7 to 42.1 (by 75%) and from to 144.7 to 139.2 (by 4%) for AvgHs_AvgApp and AvgHs_IndApp, respectively.

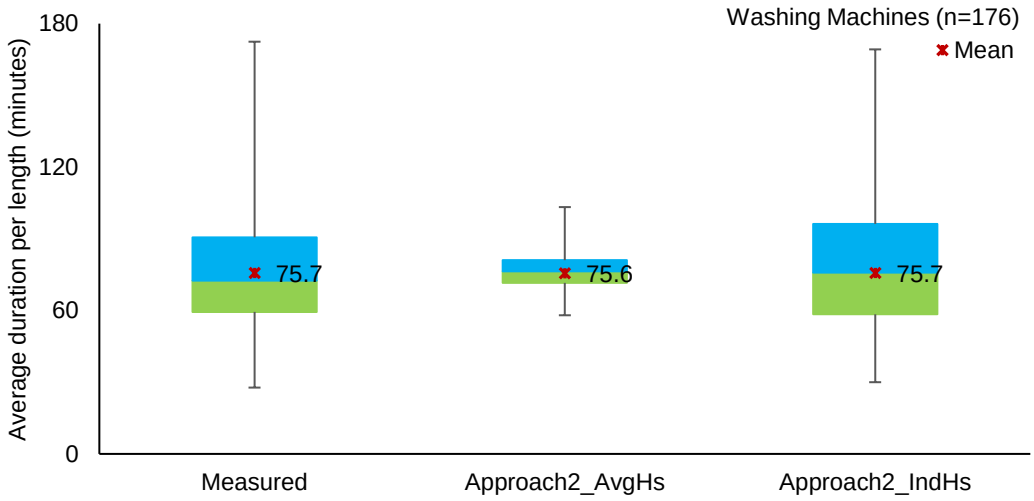


Figure 4.15.Boxplots of the average duration length per usage of washing machines resulting from one simulation compared with the measured average duration length (176 washing machines)

4.4 CHAPTER 4: SUMMARY

This chapter presented the calculation of the appliance behaviour metrics from the HES dataset and the comparison of the simulation results of appliance behaviour modelling with the measured data for each appliance behaviour metric. The conclusions of Chapter 4 are as followed:

- The HES dataset shows that there is a significant variation between households in the number of appliance switch-on events (Table 4.1) and in number of switch-on events across days (Figure 4.3).
- The results of the one-way ANOVA conducted show that there is not a significant effect of household type, occupant number and day types on the mean of average daily number of switch-on events for most of the appliances except for dishwashers. Similarly, the ANOVA test results show that there is not a significant effect of seasonality on the average daily number of switch-on events at the $p<0.05$ for the 16 appliance types except for washing machines and tumble dryers.
- There is a further variation in the switch-on times of appliances across different times of the day for all 16 appliance types (Figure 4.4). The results also show that

there is not a significant difference between the shape of the probability of switch-on times of the day among the household types (Figure 4.5).

- Duration of the appliance use is also highly variable and average household appliance durations vary significantly (Table 4.3). The results of the one-way ANOVA conducted show that there is not a significant effect of household type, occupant number and day of the week for 16 of the appliances.
- For cooking appliances and televisions, there is a significant effect of hour slots when the appliance is started on the duration of use of appliances.
- The modelling approach (Approach 2) that proposes to assign first the daily number of switch-on events, and then determines the time of the switch-on events by 'stepping through' the PDF and durations from CDFs, predicts the average daily number of switch-on events correctly (Figure 4.9 and Table 4.4). Approach 1 (similar to previous studies) does not first assign the daily number of events and simply determines the number of switch-on events and switch-on times by 'stepping through' the PDF and durations from CDFs. Approach 1 was shown to significantly underestimate the average daily number of switch-on events.
- The model variants that use individual household switch-on PDFs and individual appliance duration CDFs simulated variation in average daily number of switch-on times and durations better than those model variants developed based on averaged households and averaged appliances (Figure 4.10 and Figure 4.15).
- Approach 2 IndHs_IndApp is chosen as the best approach to model the appliance behaviour.

5 RESULT #2: POWER DEMAND MODELLING

5.1 OVERVIEW

In this chapter, the modelling of the power demand of the appliances is described. The aims of this chapter are:

- To analyse and calculate the electricity consumption and daily power demand profiles of the households.
- To analyse and calculate appliance characteristics regarding the power demand during appliance use.
- To validate the HAU model on appliance level by comparing the average daily power demand profiles of the HAU model simulation results for 16 appliances with the monitored dataset.

In Section 5.2, a detailed analysis of the yearly electricity consumption and daily power demand profiles of the households is presented and the mean values of the consumption of each appliance are compared with studies from Sweden and France. Then the individual appliance characteristics regarding the power demand during appliance use are discussed in detail. In Section 5.3, the simulation results for average daily power demand profiles for the 16 appliance types are presented and the performance of model is compared with the measured values.

5.2 CALCULATING THE POWER DEMAND FOR APPLIANCE USE

5.2.1 Electricity consumption and power demand profiles of individual households

Table 5.1 shows the summary statistics for the average measured electricity consumption per day and the estimated annual electricity consumption for the 16 appliances in the dataset. For appliance categories, electric showers have the highest average daily electricity consumption, a mean of 0.90 kWh per day based on the 73 electric showers in the dataset. Televisions have the lowest average daily electricity consumption with a mean of 0.44 kWh per day. Fridge-freezers have the highest average daily electricity consumption with a mean of 1.16 kWh per day based on the 129 fridge-freezers in the dataset. This is followed by tumble dryers with a mean of 1.09 kWh per day based on the 86 tumble dryers in the dataset. The results highlight the variation in average daily electricity consumption for all appliance types. For example, the results show that one washing machine has an average daily electricity consumption of 3.70 kWh per day throughout its monitoring period (the highest observed in the dataset for washing machine) and another had an average of 0.09 kWh (the lowest observed). Similarly, one TV1 has an average daily electricity consumption of 2.13 kWh per day throughout its monitoring period (the highest observed in the dataset for televisions) and another had an average of 0.01 kWh (the lowest observed). Grills have the lowest average daily electricity consumption, a mean of 0.04 kWh per day based on the 5 grills in the dataset. The results show that the larger the sample size, the smaller the confidence interval is. For example, washing machines (n=176) have a mean of 0.45 kWh per day of electricity consumption of with ±0.05 (95% confidence interval) whereas the washing-drying machines (n=18) have a mean of 0.75 average daily electricity consumption with ±0.39 (95% confidence interval). This indicates the importance of high sample size for estimating the switch-on statistics.

Table 5.1 Analysis of electricity consumption of the appliances with cycles monitored in the Household Electricity Use Survey

Appliances			Average measured electricity consumption per day (kWh/day)[1]					Estimated annual electricity consumption (kWh/year)[2]
Category	**Types**	**n[3]**	**Mean[4]**	**95% C.I of the mean**	**Min**	**Max**	**Med**	**Mean**
Wet appliances	Washing machine	176	0.45	±0.05	0.03	1.90	0.36	163.2
	Washing-drying machine	18	0.75	±0.39	0.09	3.70	0.61	275.1
	Tumble dryer	86	1.09	±0.24	0.02	6.74	0.79	398.8
	Dishwasher	84	0.80	±0.09	0.06	1.93	0.78	293.7
	All	364	0.70	±0.07	0.02	6.74	0.49	253.9
Cooking appliances	Cooker	105	0.91	±0.13	0.01	3.22	0.72	332.3
	Oven	44	0.61	±0.14	0.00	1.55	0.53	223.9
	Hob	9	0.58	±0.22	0.24	1.38	0.53	212.7
	Grill	5	0.04	±0.02	0.01	0.05	0.04	12.8
	All	163	0.78	±0.10	0.00	3.22	0.62	286.2
Televisions	TV1	86	0.54	±0.11	0.01	2.13	0.38	196.9
	TV2	44	0.34	±0.13	0.00	1.32	0.12	125.9
	TV3	21	0.19	±0.12	0.00	0.92	0.09	69.1
	All	151	0.44	±0.08	0.00	2.13	0.27	160.6
Electric shower		73	0.90	±0.21	0.02	3.93	0.53	329.2
Cold appliances	Fridge	88	0.45	±0.05	0.14	1.40	0.41	164.8
	Fridge-freezer	129	1.16	±0.10	0.44	3.43	1.00	423.2
	Upright freezer	81	0.87	±0.10	0.15	2.30	0.76	315.9
	Chest freezer	34	0.89	±0.15	0.31	2.04	0.81	325.7
	All	332	0.87	±0.06	0.14	3.43	0.77	318.6

The datasets of monthly monitored households (Agd1-a,b,c,d) and yearly monitored households are used to calculate for the average measured electricity consumption per day. It is calculated by dividing the total electricity consumption from the washing machines by the monitored number of days.

[2] The estimated annual electricity consumption is calculated by multiplying the average measured electricity consumption per day values with 365 days/year.

[3] Not all houses own every appliance, n indicates the number of houses with the corresponding appliance.

[4] Mean is calculated from the individual average measured electricity consumption per day of the homes.

Figure 5.1 shows the distribution of the estimated annual electricity consumption (kWh/year) with box plots which were calculated using a method of simple multiplying the measured electricity consumption per day values with the number of days in a year (365). The results support the argument that there is a variation in average daily electricity consumption for all appliance types.

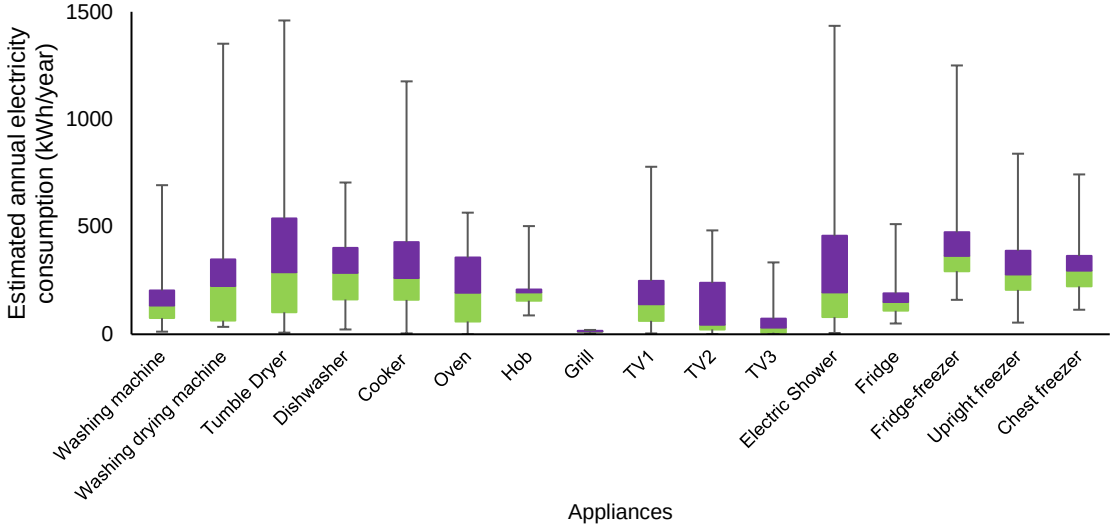


Figure 5.1 Boxplots of the estimated annual electricity consumption (kWh/year) for the 16 appliance types

These estimated annual electricity consumption results of wet appliances and cold appliances are compared to reported values in previous studies of the Remodece monitored campaign (100 households were monitored for one year during 2007) and SWE400 project in Sweden (End-use metering campaign in 400 households from August 2005 to December 2007) (Table 5.2).

Table 5.2 Comparison of the yearly electricity consumption (kWh) of some of the individual appliances with two other studies Remodece and SWE400

Appliance types	Yearly electricity consumption (kWh)		
	HES	Remodece	SWE 400
Washing machines	163	169	205
Dishwashers	284	273	175
Fridge	164	253	213
Fridge-freezer	423	460	469

Figure 5.2 shows the histogram of the estimated annual electricity consumption (kWh/year) for the 16 appliances. The graphs show a skewed distribution and it is clear that the higher the estimated annual electricity consumption (kWh/year), the less frequent are the appliances. The frequency of the appliances significantly decreased after 800 kWh/year for wet appliances and cold appliances. This value was 400 kWh/year for cooking appliances and televisions. For almost 80% of the electric showers, the estimated annual electricity consumption was under 400kWh/year.

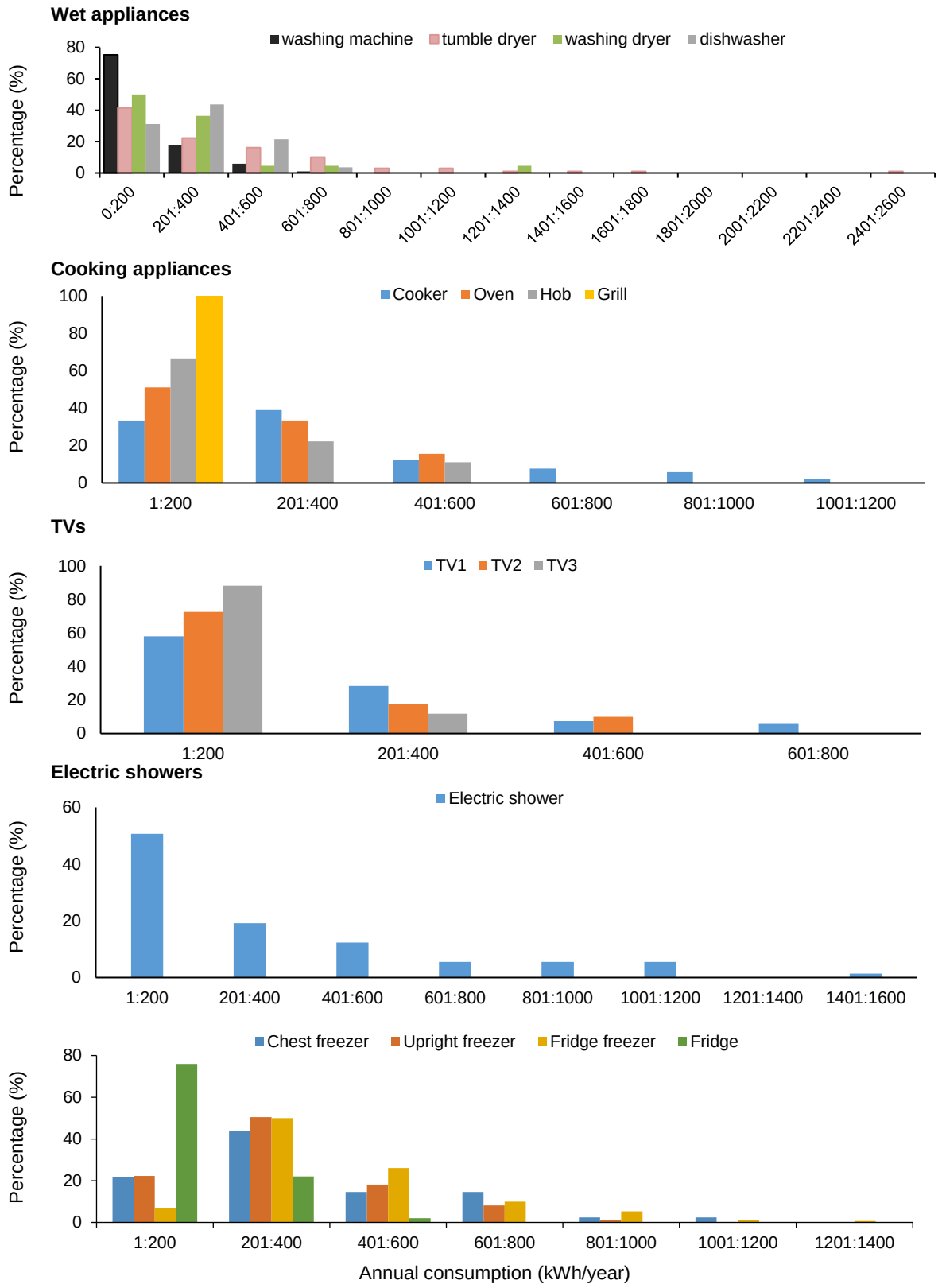


Figure 5.2 Histogram of the estimated annual electricity consumptions of the appliances with cycles. Washing machines (n=176), washing-drying machine (n=18), tumble dryer (n=86), dishwasher (n=84), cooker (n=105), oven (n=44), grill (n=5), hob(n=9), TV1(n=86), TV2(n=44), TV3(n=21), electric shower(n=73), fridge(n=88), fridge-freezer(n=129), upright-freezer(n=81), chest-freezer(n=34).

Figure 5.3 shows the mean power demand (W) varying over daily profiles for the 16 appliance types. These profiles are shown in here for half-hourly time slots due to demonstrate the overall trend of the profiles. The results highlight the differences that occur in mean power demand (W) across appliance categories and appliance types.

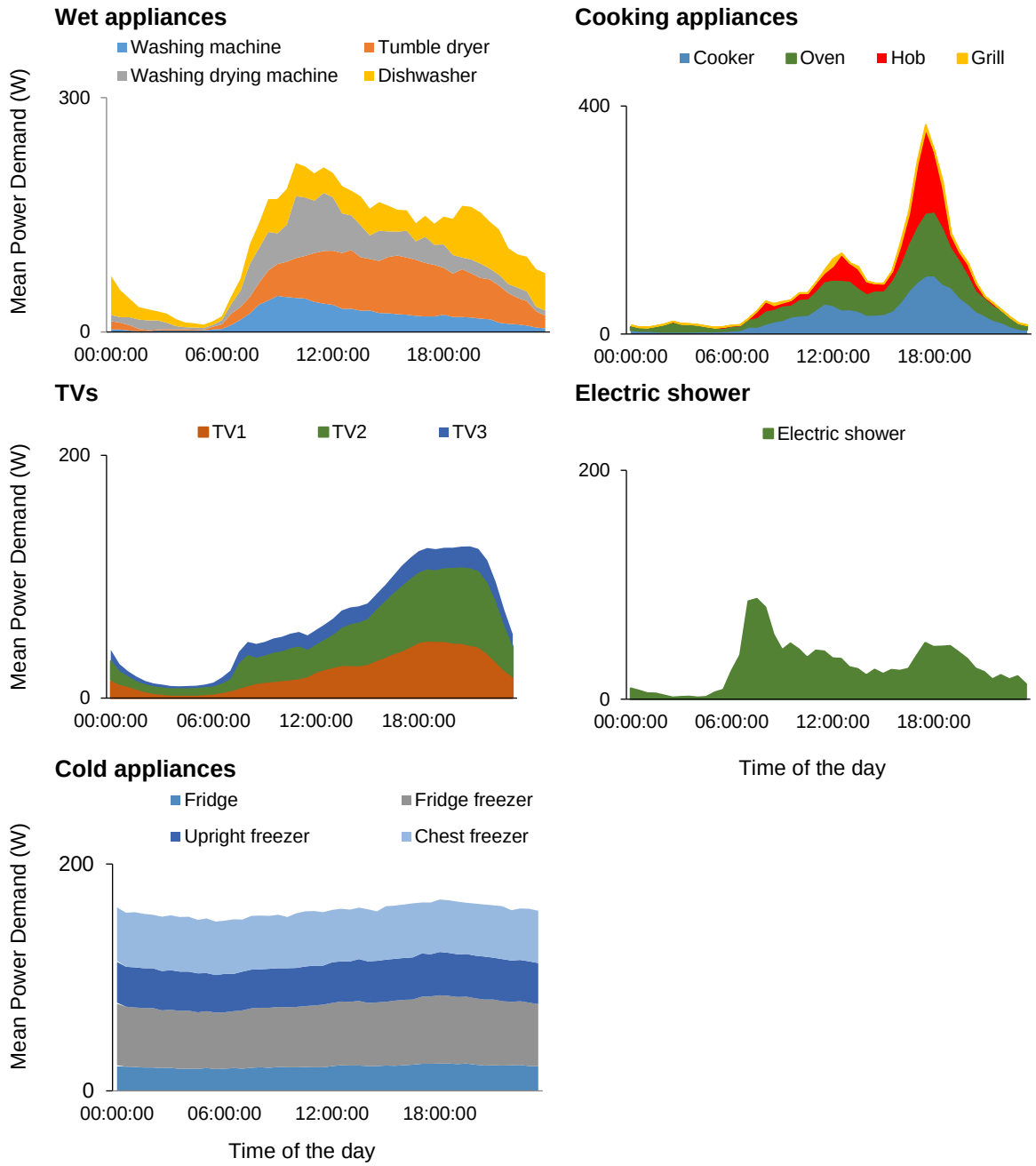


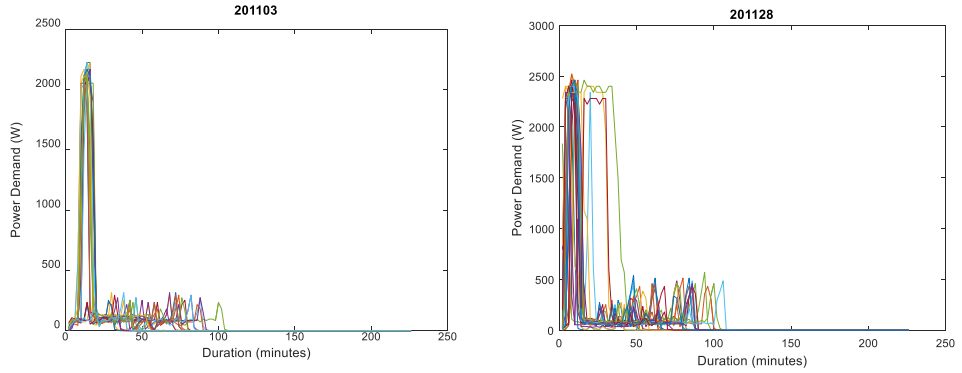
Figure 5.3 Comparison of the mean half hourly power demand of the appliance categories plotted in stack area: wet appliances, cooking appliances, televisions, electric showers and cold appliances in 2011 Household Electricity Survey (HES)

The figures show that different appliances contribute to the total mean power demand at different times of the day. Mean power demand of the cooking appliances are highest around morning, noon and evening times which are presumably meal times. Peak power demand occurs in the evening for dishwashers after the evening meal, whereas the peak time for washing machines and washing-drying machine is observed in the morning. Mean power demand of tumble dryers is high starting from noon, probably after the washing machines are finished in the morning. Mean power demand of the cold appliances are constant throughout the day. Televisions are switched-on starting from the early morning. For electric showers, the peak times occur in the morning and in the evening.

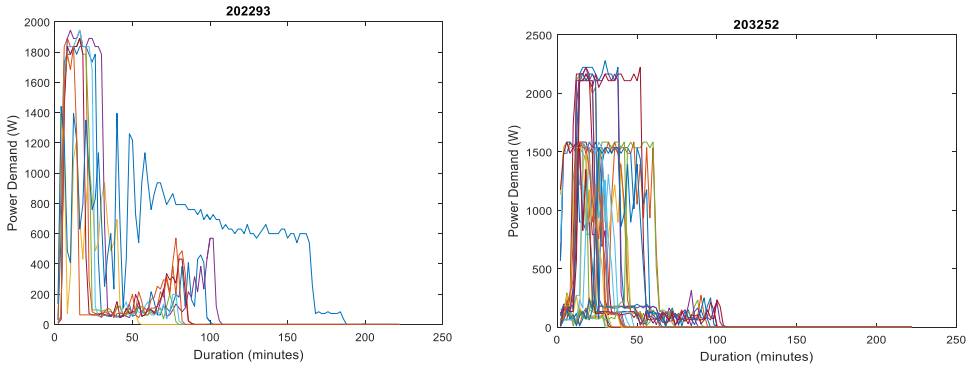
5.2.2 Power demand characteristics of each individual appliance per usage

Figure 5.4 shows the examples of power demand of the cycles (power demand recording over time during the usage) of wet appliances observed for two households (see Appendix C to see the washing machines for 176 households, washing-drying machines for 18 households etc.). The figures show that the power demand levels for the wet appliances are not constant during the usage, and the power levels change during different stages of the cycle. For example, washing machines have two distinct sections; a main cycle and an end section. The main cycle is with a power draw of between 1,200-2,400 Watts. This is the part where the water is heated up to the desired temperature by a resistant heating system. The end period is generally much longer as cleaning takes place for some time. At the end of the cycle the power demand increases for the last spin in the washing machines where the drum is rotated at a high speed to extract the water from the load and to reach a dry load at the end of the programme. The figures also show that the shapes of the power demand profile for each usage are not identical. For example, sometimes heating period of the washing machine takes longer, or spinning starts at a different time. This is due to the fact that the occupant chooses different programmes during each usage. It can be seen that the durations and power demands of these distinct sections change according to the choice of temperature and the spin speeds under various programmes.

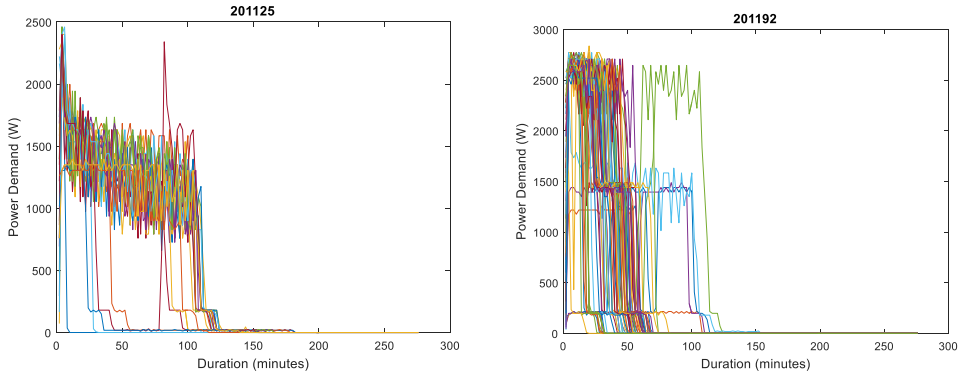
Washing machines



Washing-drying machines



Tumble dryers



Dishwashers

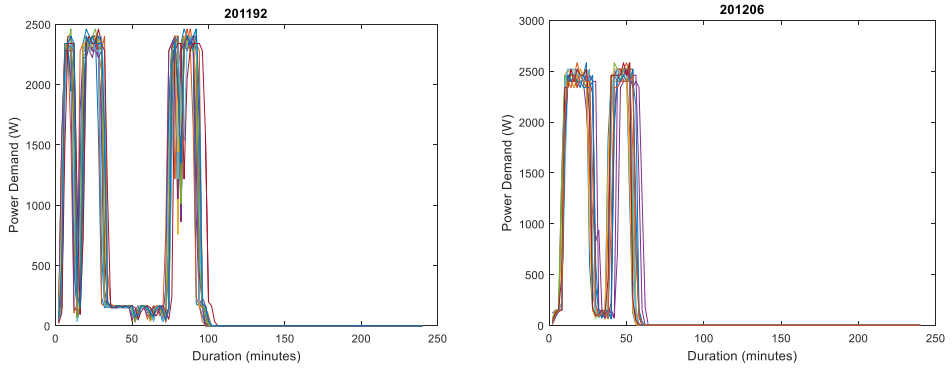


Figure 5.4 Examples of power demand profiles of the wet appliances for each usage for several households of the HES dataset

Figure 5.5 shows the box plots of average power per cycle of the wet appliances.

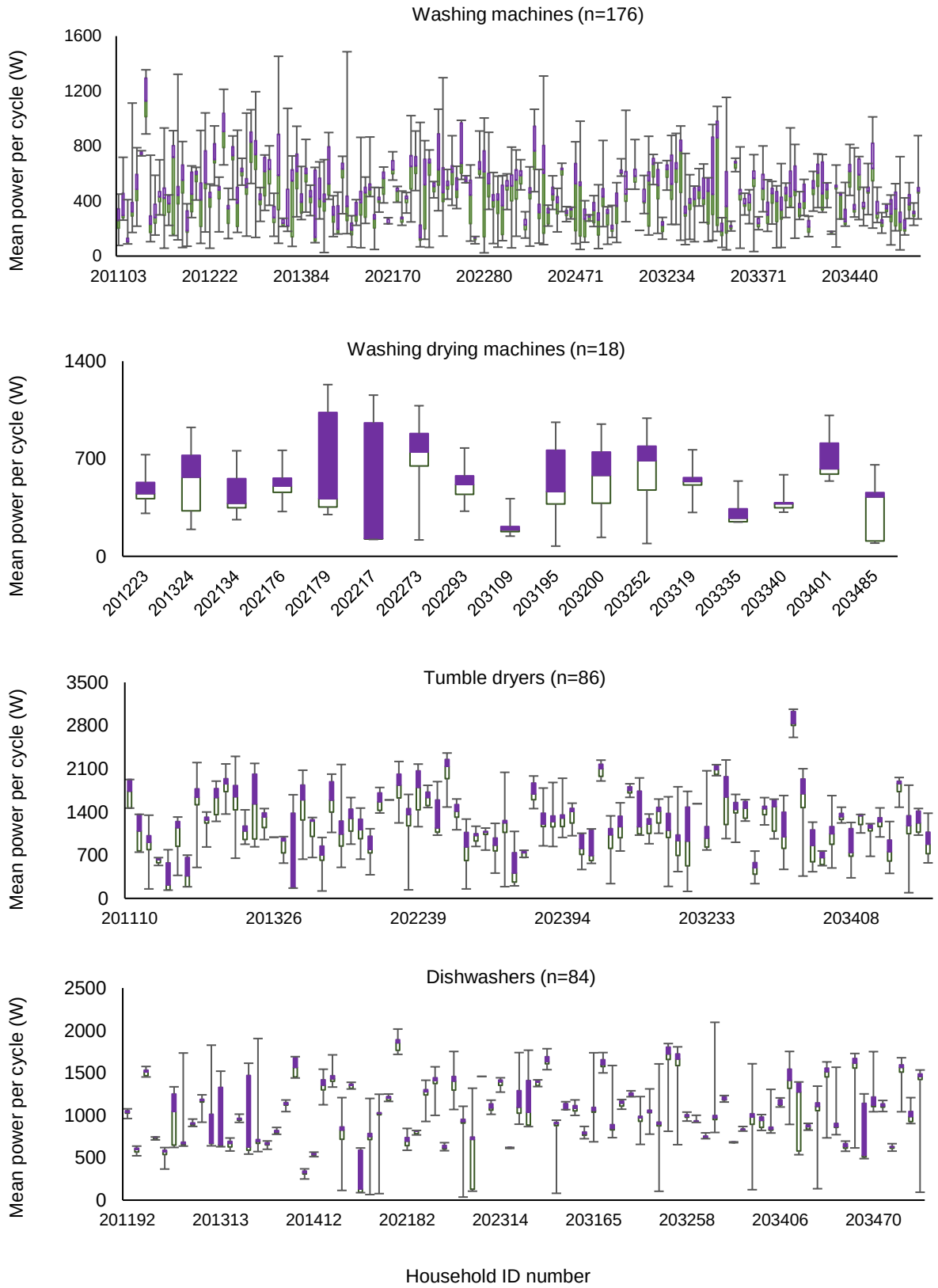
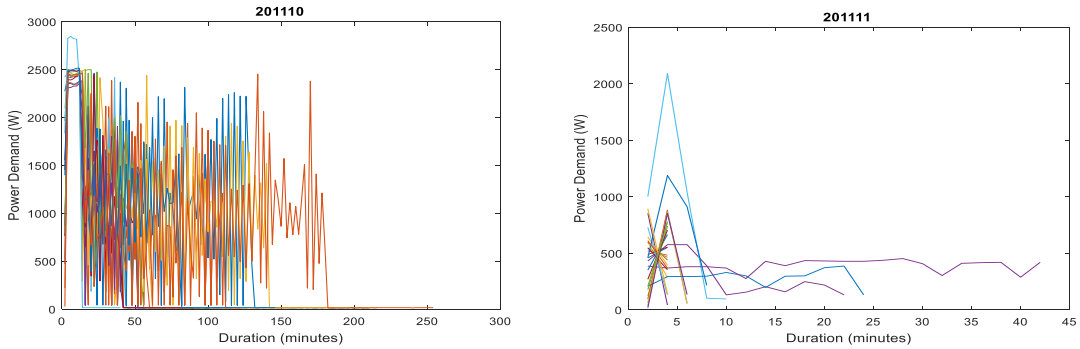


Figure 5.5 Box-plots of the mean power per cycle of wet appliances

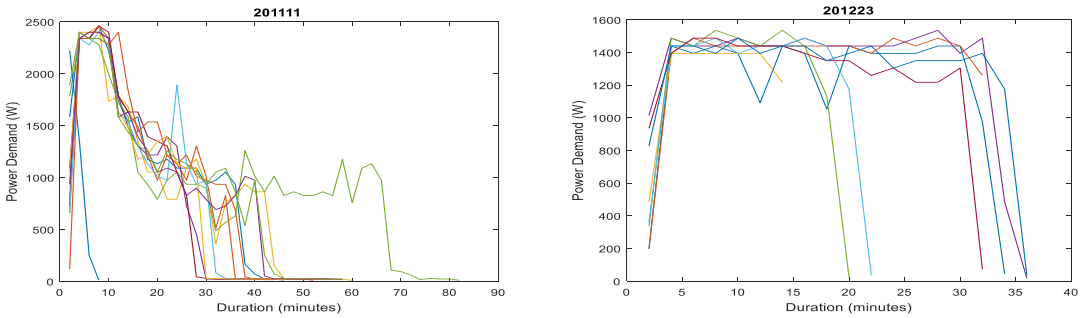
Box plot of mean power per cycle of wet appliances are created for every household who owns the appliance. (176 washing machines, 18 washing-drying machines in the figures). It is important to note that the values in Figure 5.5 are mean power demand per cycle calculated by averaging the power demand during appliance use shown in Figure 5.4. Figure 5.5 shows that the range of mean power was high for some appliances. For example, the mean power demand range was high for laundry appliances which are washing machines, washing-drying machines and tumble dryers. This could be due to the fact that there are more variables that can affect the power demand of each cycle which could be choice of programme, weight of the clothes, temperature of the wash etc. For dishwasher, this range is almost non-existent or very small compared to laundry machines meaning that households preferred a similar choice of programmes for each usage and the number of dishes did not affect the power demand profiles of the dishwashers.

Figure 5.6 shows the examples of power demand during the use of cooking appliances observed for two households. The figures show that the power demand levels for the cooking appliances changed due to thermostatic controls during the usage compared to the wet appliances. Wet appliances have more structured stages such as heating, spinning etc. The cooking appliance mostly follow a constant high power level between switch-on and switch-off moments. However, the settings were sometimes changed during the cooking such as decreasing the temperature of the oven or changed to lower level of the hob which affected the power demand level. After the cooking activity, the hobs, cooker and grills are switched off. For some of the ovens, mostly the fans were still on and the power levels dropped significantly and stayed constant round 12 W to 15 W before it was completely off. This analysis gives important insight into the power demand during use of a cooking appliance. In literature, these profiles were mostly accepted as constant (Richardson et al., 2006; Widén et al., 2009), however, the analysis of the cooking appliances show that this is not the case and power demand levels change during use.

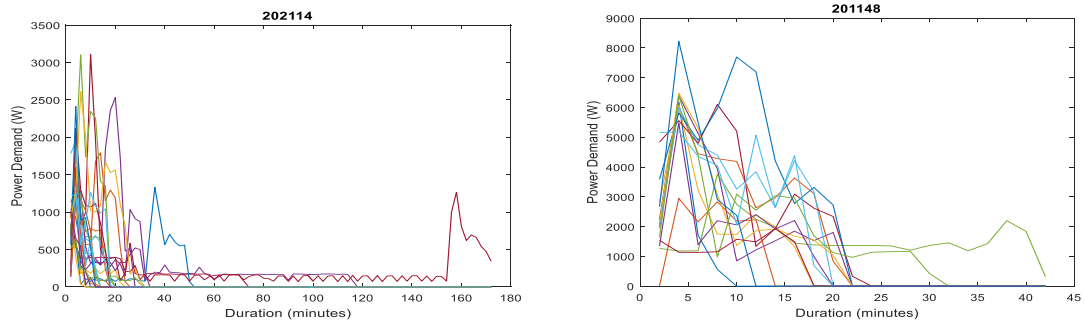
Cookers



Ovens



Hobs



Grills

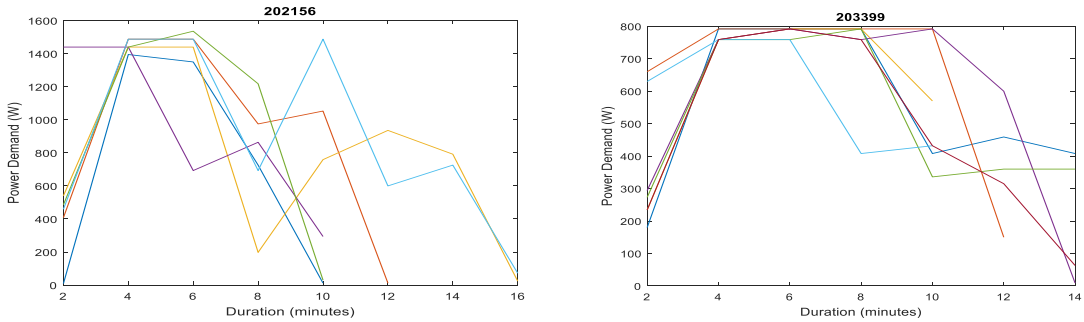


Figure 5.6 Examples of power demand profiles of the cooking appliances for each usage for several households of the HES dataset

Figure 5.7 shows the box plots of average power per cycle of cooking appliances.

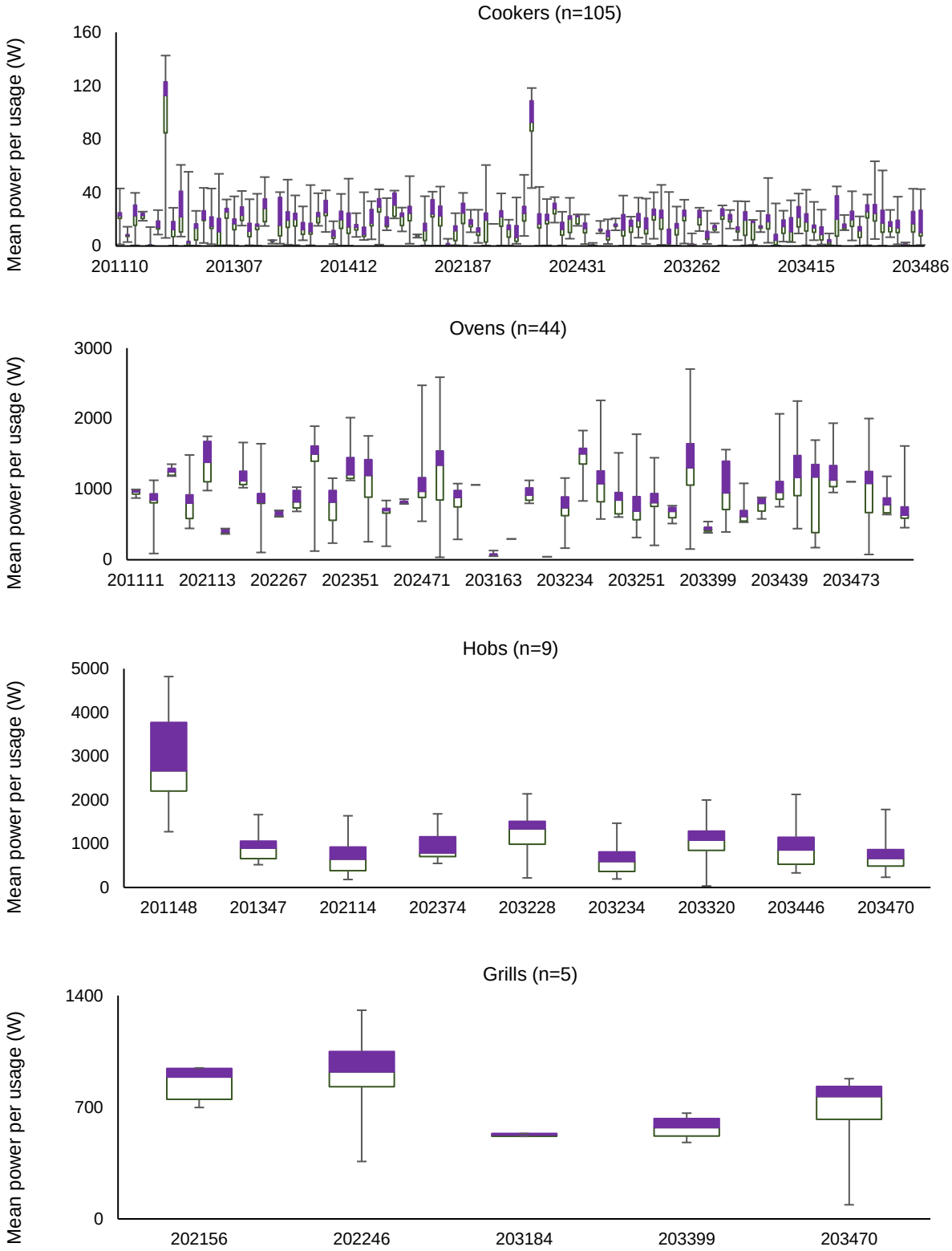


Figure 5.7 Box-plots of the mean power per cycle of cooking appliances

Similarly, it is important to note that the values at Figure 5.7 are mean power demand per usage. Figure 5.7 shows that the range of mean power is high for cooking appliances as well. This means that the households have used different settings such different temperature options for each usage. This has caused mean power for usage different per usage.

Figure 5.8 shows the examples of power demand during the use of televisions and electric showers observed for two households. The figures show that the power demand levels are mostly constant during the usage although power levels fluctuate during the usage. For example, for the television in the household with ID number 201103, power demand fluctuates between 120 W and 136 Watts. Throughout their usage, although the duration length of the usage changes, the power demand was similar for each usage especially for televisions in comparison to other appliances.

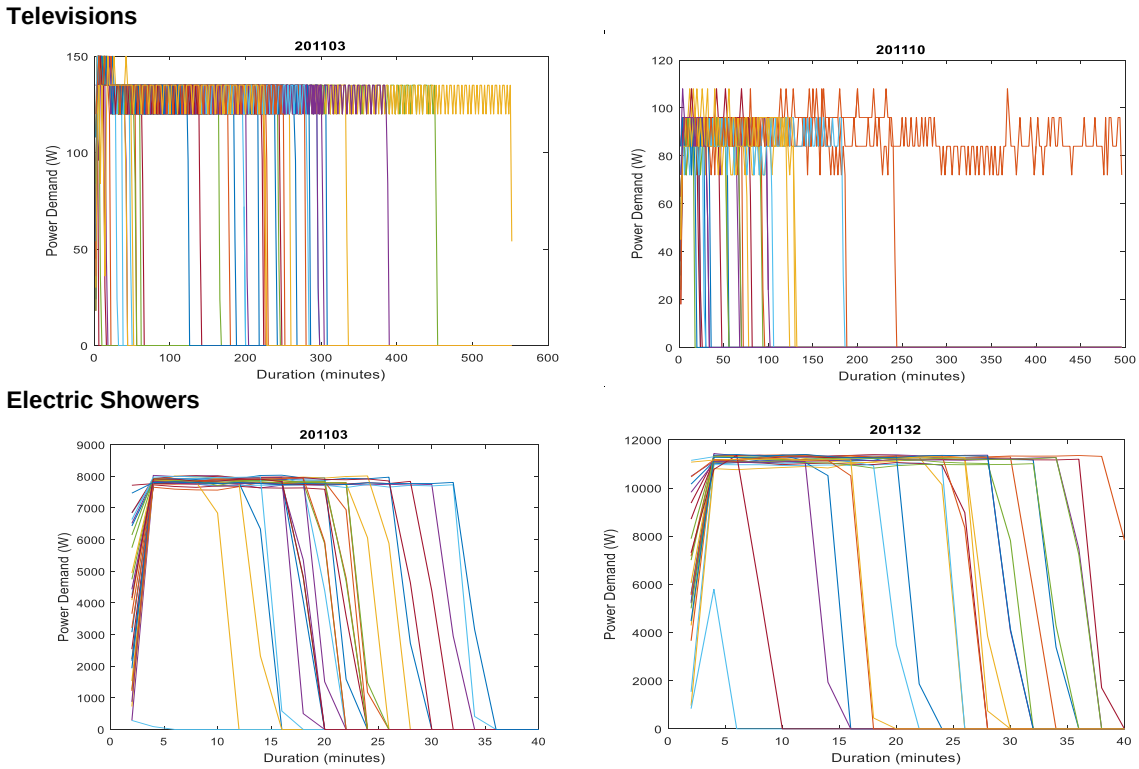


Figure 5.8 Examples of power demand profiles of the televisions and electric showers for each usage for several households of the HES dataset

Figure 5.9 shows the box plots of mean power per usage of TV1 and electric showers. TV2 and TV3 are not shown as they are the same appliance type as TV1. The range of mean power per each usage of televisions range is almost non-existent or very small compared to wet and cooking appliances meaning that although the duration of the use of TV1 changes, the power demand stays almost constant. For electric showers, the mean power changed per usage resulting in a range of values per usage. This may be due to households preferring different settings for showering.

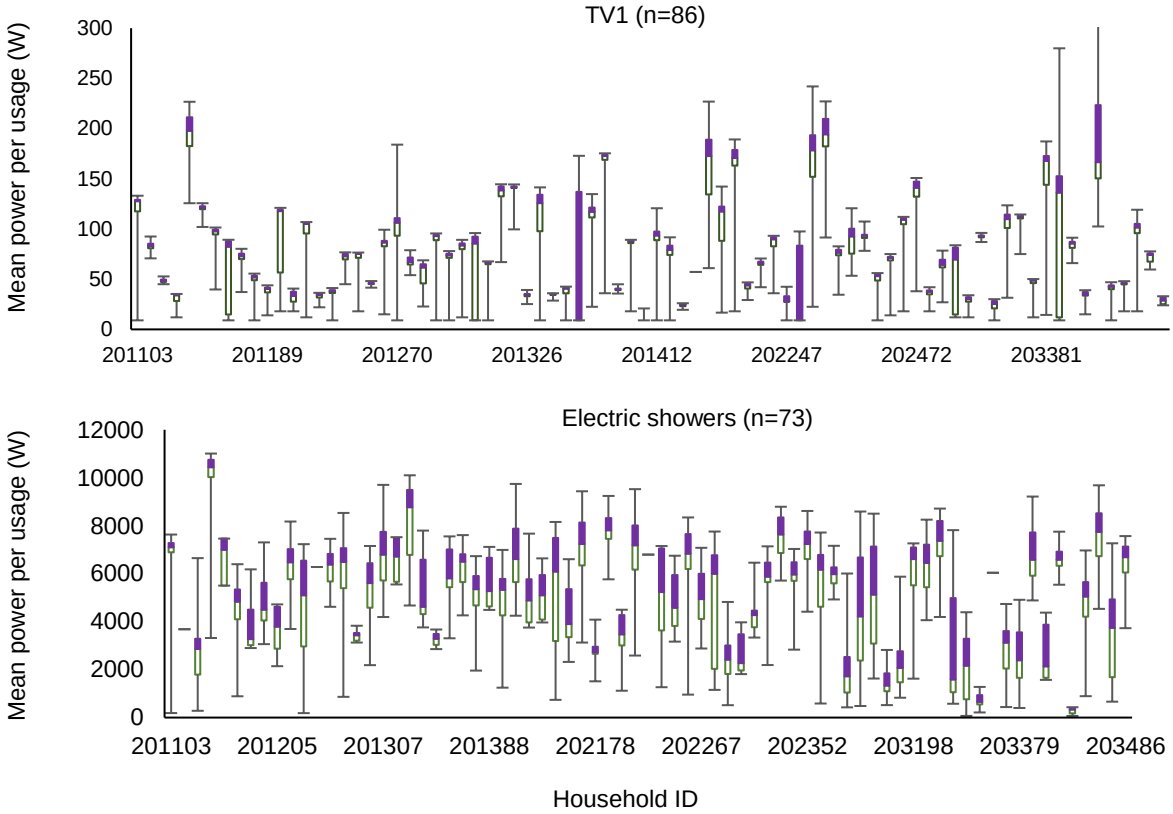
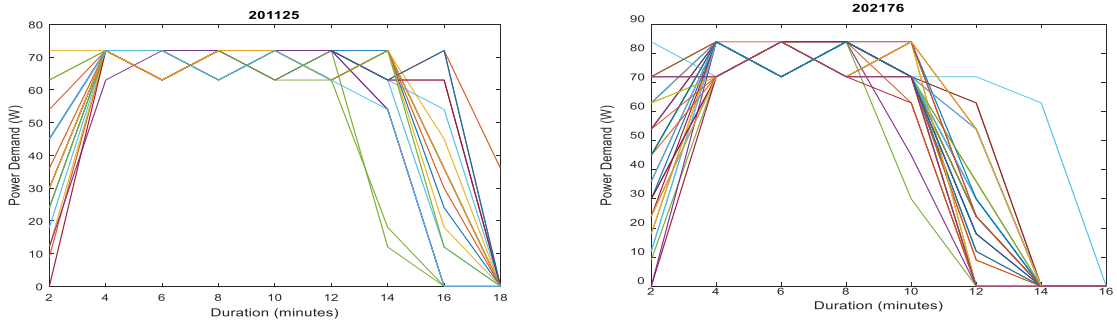


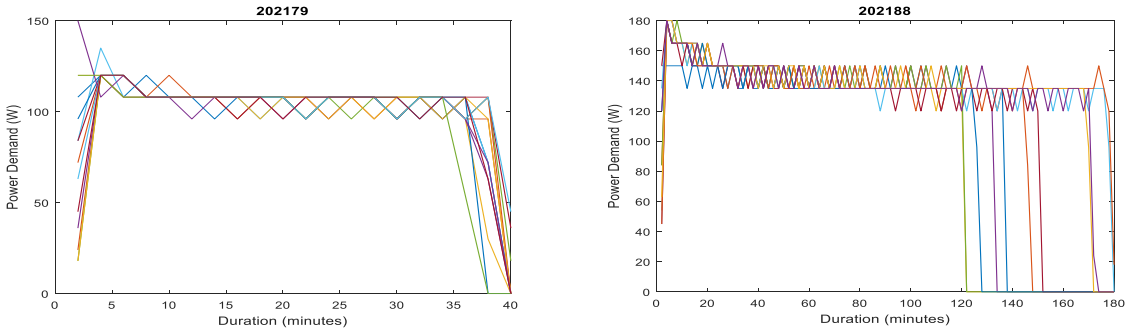
Figure 5.9 Box-plots of the mean power per cycle of televisions (TV1 only in the graph) and electric showers.

Figure 5.10 shows the examples of power demand of sequences of cold appliances observed for a day for two households. Cold appliances are in use continuously and the user has no direct interaction with the switch-on or switch-off times however the duration is affected by occupant's door opening or storing food inside. The figures show that the power demand is constant when the compressor is on. Also, similar to televisions, the power levels were almost identical for each sequence during the day although the duration of the sequence changes.

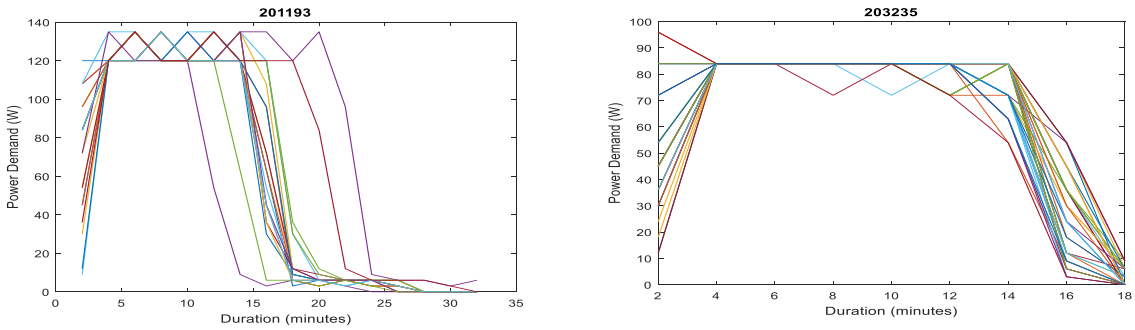
Fridges



Fridge freezers



Upright freezers



Chest freezers

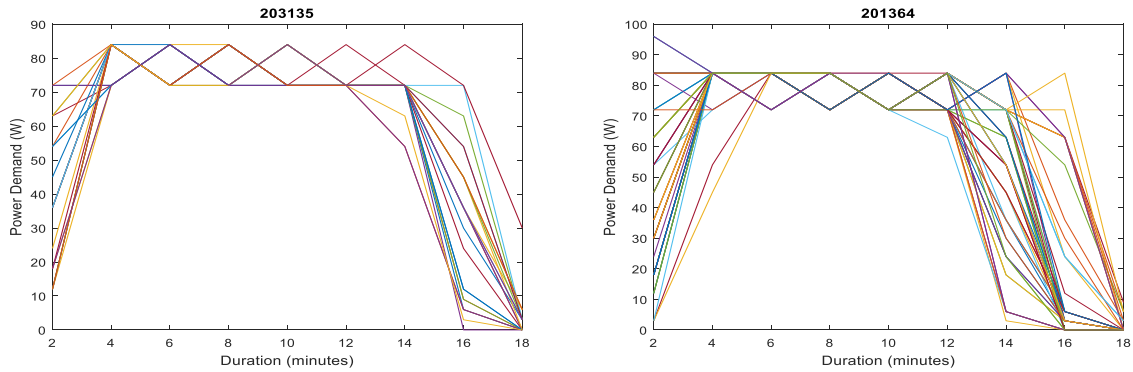


Figure 5.10 Examples of power demand profiles of the cooking appliances for each usage for several households of the HES dataset

Box plots of mean power per sequence of cold appliances are created for every household who owns the appliance (88 fridges and129 fridge freezers presented in the figures). The literature shows that in contrast to refrigerators, freezers are exposed to less user actions; their electricity consumption is less affected by door openings or new food stored (R. Stamminger and Rheinische Friedrich-Wilhelms-Universität Bonn, 2008). The HES monitored both chest freezers and upright freezers. It can be seen from the Figure 5.11 that the mean power is not affected significantly as opening the doors affects mostly the duration of the compressor run not the power demand during when the compressor is on.

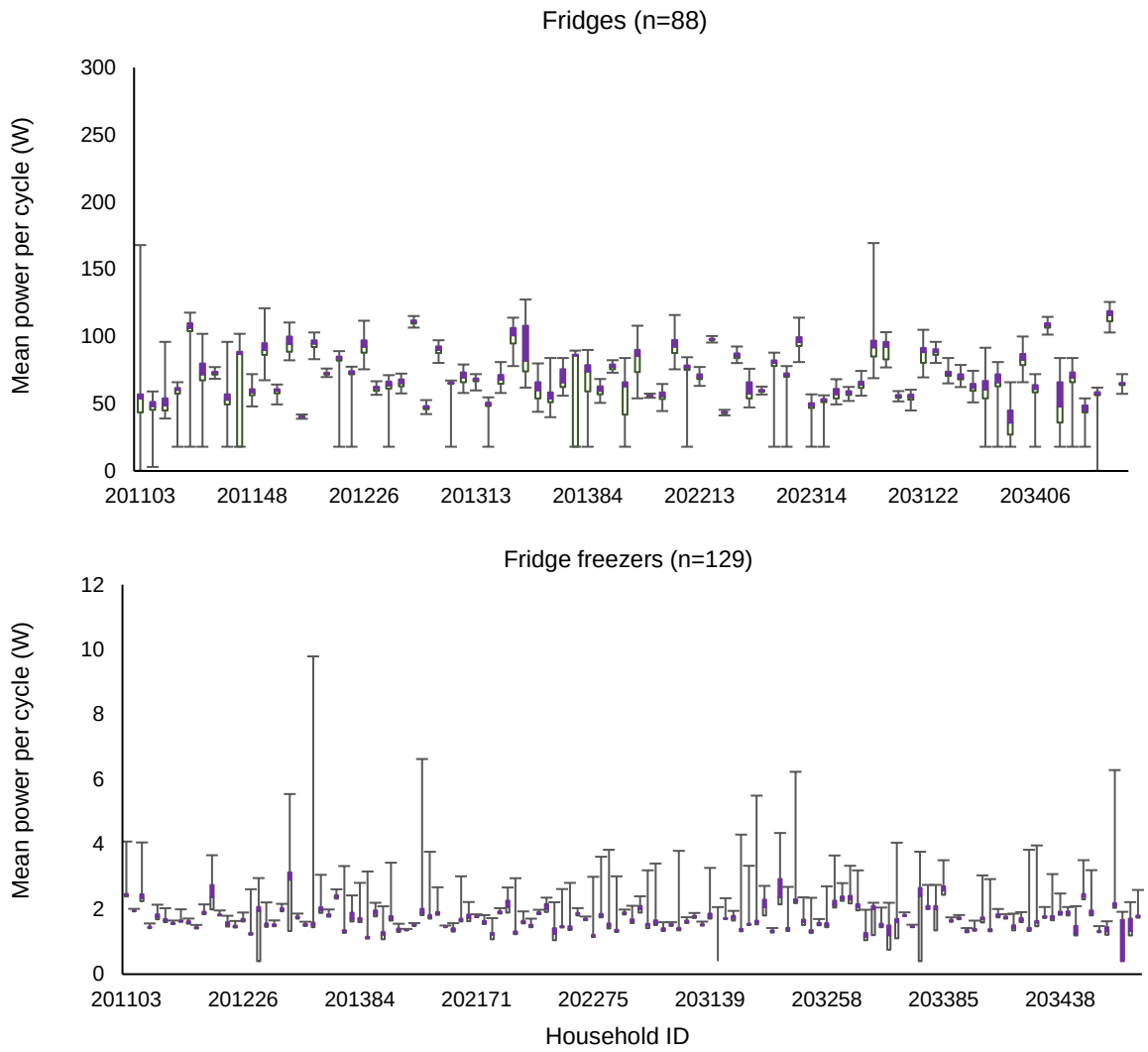


Figure 5.11 Box-plots of the mean power per cycle of fridge freezers

5.3 SIMULATION RESULTS

The simulation period and time resolution were chosen to be the same as in the HES dataset. This means that the electricity demand profiles of 225 the households have been generated exactly the same with the monitoring period in Figure 3.5 by applying the household appliance usage model (HAU model) assigning power demand profiles (e.g. 176 households with washing machines for 27 days; 86 households with tumble dryer for 28 days etc.). The performance of the simulations is evaluated by comparing the daily electricity demand profiles to those of the measured HES dataset. For this purpose, the mean values of the 100 simulations are compared with the mean measured value to assess the average profile of an aggregate population. In addition, box plots are shown to show the variety of electricity demand profiles between the households. Chapter 4 concludes that Approach2_Ind_Hs_Ind_App ('IndHs' denotes the use of an individual household CDF of number of switch-on events and PDF of switch-on times and 'IndApp' use individual appliance CDFs of durations) was the best approach for modelling the appliance use in terms of predicting the switch-on times of the day and number of switch-on times. Therefore, only the electricity demand profiles of the households developed by using the Approach2_IndHs_IndApp of the HAU model is used in the comparison with the measured values of the HES dataset.

5.3.1 Comparison of the daily mean electricity profiles of appliances

Figure 5.12 shows the comparison of the mean half-hourly power demand profiles of wet appliances simulated using the Approach2_IndHs_IndApp of 100 simulations and measured values. Figure 5.12 shows that the simulation results do not exactly match with the measured peak power demands although the HAU model was successful at predicting the number of switch-on times of the day (see Figure 4.11). The mean half-hourly electricity demand profiles were predicted close to the measured values. It is also important to see that the model is good at accounting the power demand profiles continued from the previous day which can be seen 00:00 to 02:00. The switch-on events at these time slots are very low (see Figure 4.4). However, there is power demand due to the appliance started in the previous day. This is very important

to consider for dishwashers as most of the dishwashers continued overnight as they were switched-on quite late compared to other wet appliances. The figure also shows that although the model predicts the appliance behaviour metrics quite accurately (see Section 4.3.2), there are discrepancies predicting the power demand profiles. This may be partly due to stand-by power and decisions made regarding where the cycle ends. The measured average is calculated by taking the average of the core data where stand-by power exists. However, stand-by power was not considered in this study and the cycle of the wet appliances are determined to be finished before the appliance switches off and stand-by starts.

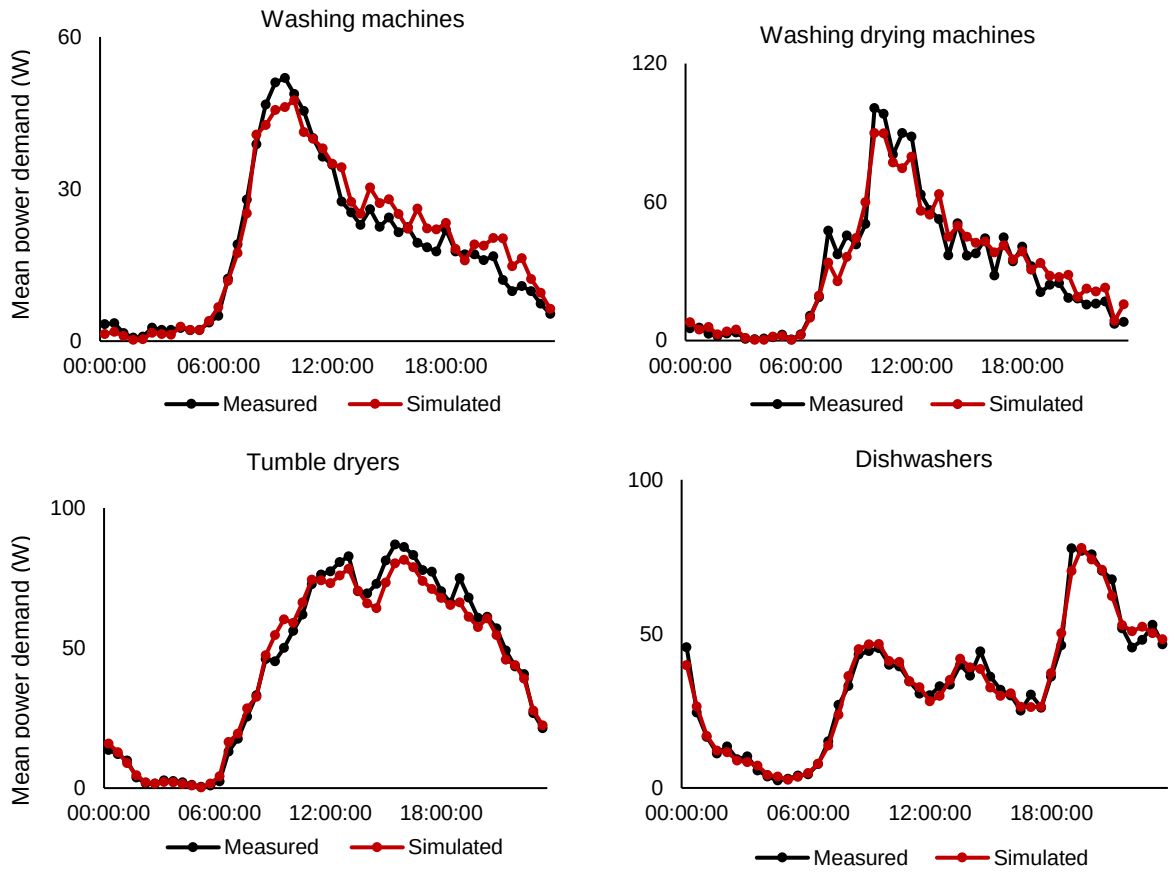


Figure 5.12 Mean half-hourly power demand profiles of wet appliances (The simulated values are calculated using the Approach2_Ind_Hs_Ind_App).

Figure 5.13 shows the percentage difference which was calculated for washing-drying machines and tumble dryers for every 30-minute time step. The percentage error was calculated by subtracting the simulation result from the measured value and dividing it by the measured value. The percentage error is quite high for early in the mornings or late at nights, as these values are quite small (less than 10 W). Therefore, only 1 W difference can lead to 80% percentage error. The percentage difference is less 10 % for peak hours for every half-hourly time-steps.

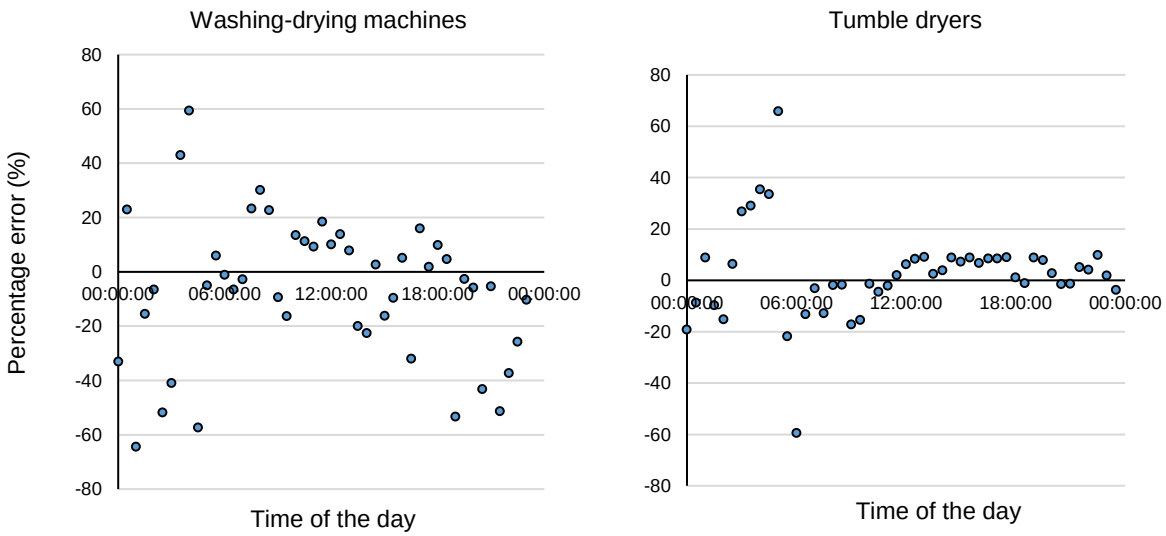


Figure 5.13 Percentage error of the daily power demand profiles for washing-drying machines and tumble dryers.

Figure 5.14 shows the comparison of the mean half-hourly power demand (W) of the cooking appliances over a day and measured values. The appliance electricity model does comparatively well in predicting the electricity demand. However, it is also clear that the values predicted by the appliance model vary from those measured, sometimes overestimating and sometimes underestimating. The peaks of the measured and the simulated values are close to each other however mostly slightly underestimated.

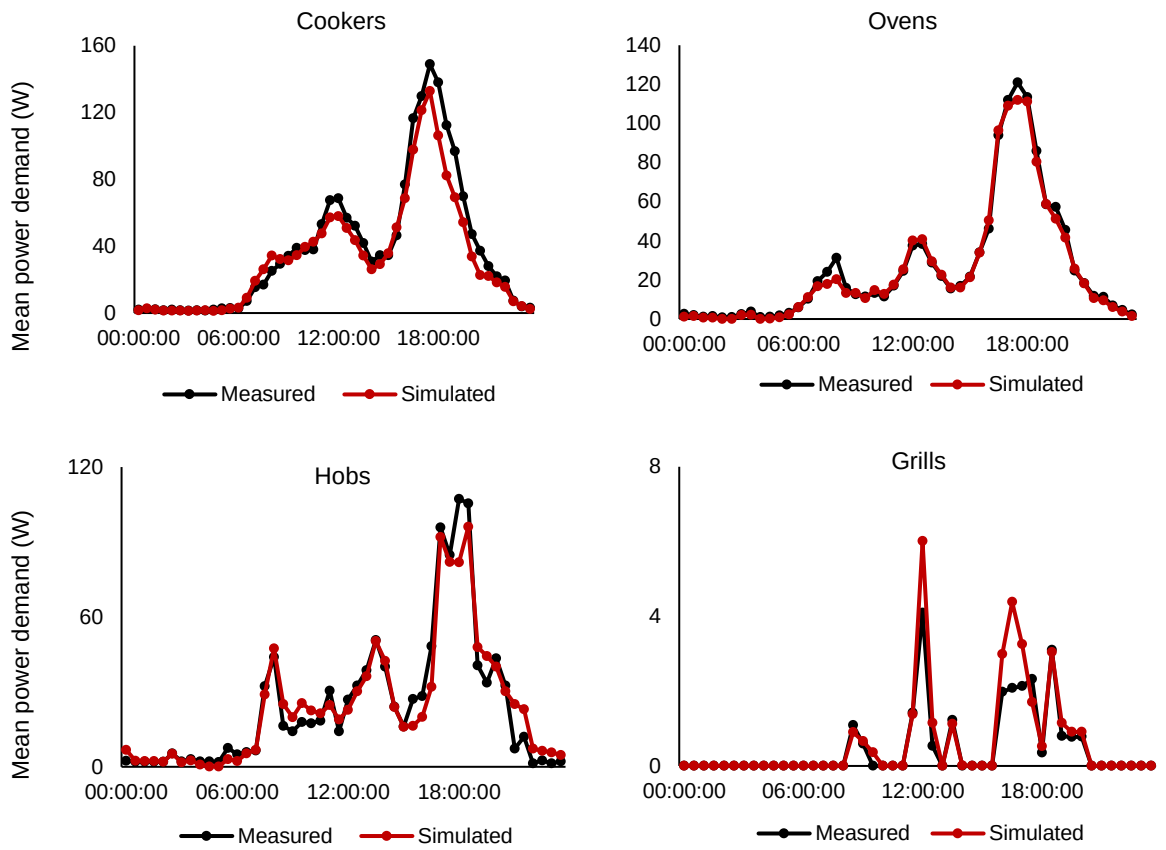


Figure 5.14 Mean half-hourly power demand profiles of cooking appliances (The simulated values are calculated using the Approach2_Ind_Hs_Ind_App).

Figure 5.15 shows the comparison of the mean half-hourly power demand (W) of the televisions and electric showers appliances over a day and the measured values. For televisions, the mean power demands of peak load were underestimated up to 14-16% for televisions (TV1, TV2 and TV3). Electric showers were predicted with a very small error. The reason for this can be explained by the duration distributions. Although the model predicts the number of switch-on events close to the measured values due to condition added by Step 1 (see Section 3.2) for predicting the number of switch-on events (see Section 4.3.1), duration distribution is a significant factor when the duration of the activity is long. For example, the mean of durations per TV1 usage (160.2 minutes) is significantly higher than electric showers (9.44 minutes). The long duration length of television can cause the discrepancies. This is discussed more in details in Section 5.3.2.

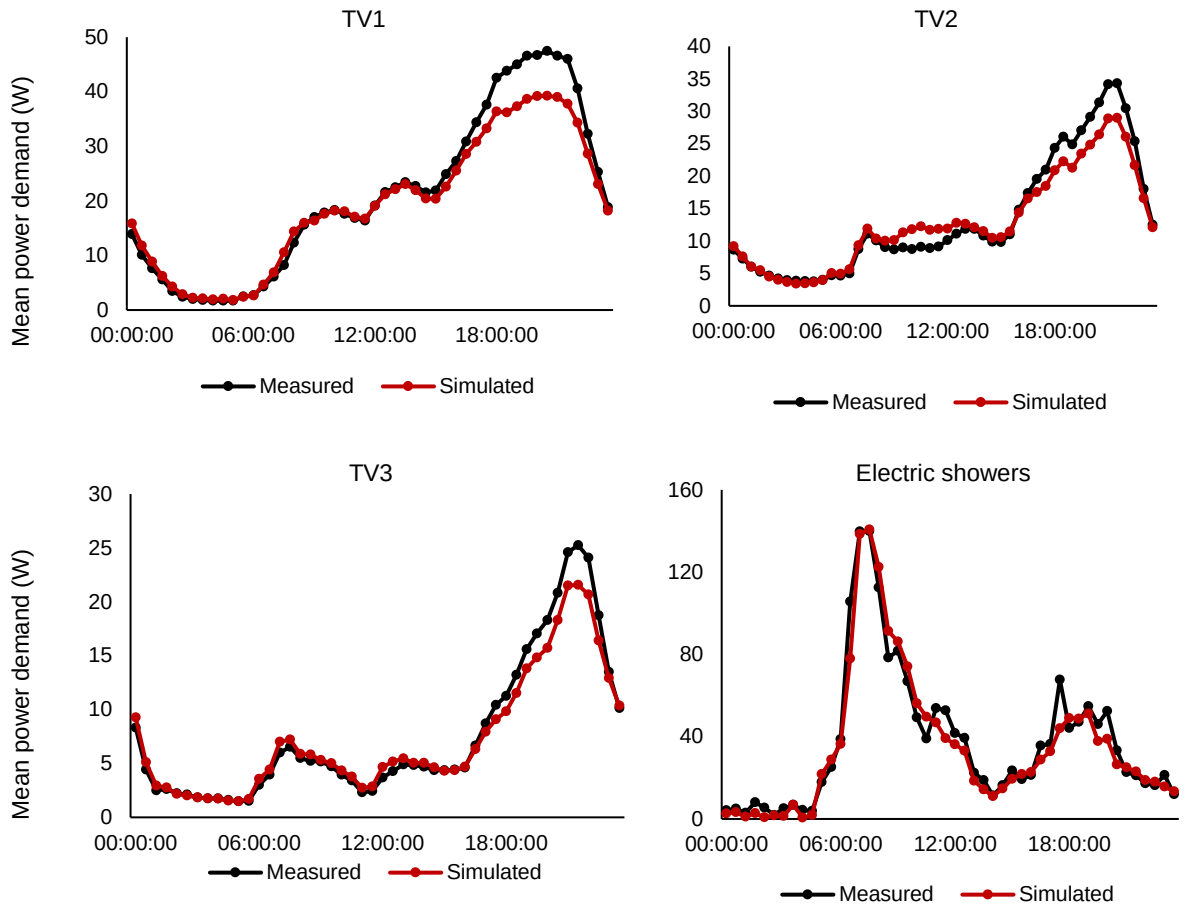


Figure 5.15 Mean half-hourly power demand profiles of TVs and electric showers (The simulated values are calculated using the Approach2_Ind_Hs_Ind_App).

Figure 5.16 shows the comparison of the mean half-hourly power demand (W) of the cold appliances over a day and the measured values. For cold appliances, the modelling took longer time to model the power demand profiles, as the number of switch-on events for a day is much higher compared to the other appliance types. For example, for chest freezers, the average number of switch-on events ranges between 5.50 to 109.7 times per day whereas for cookers it is 2.09 times per day. The graphs show that power demand profiles were predicted poorly compared to the other appliances. The discrepancies were up to 10 % for several time-steps.

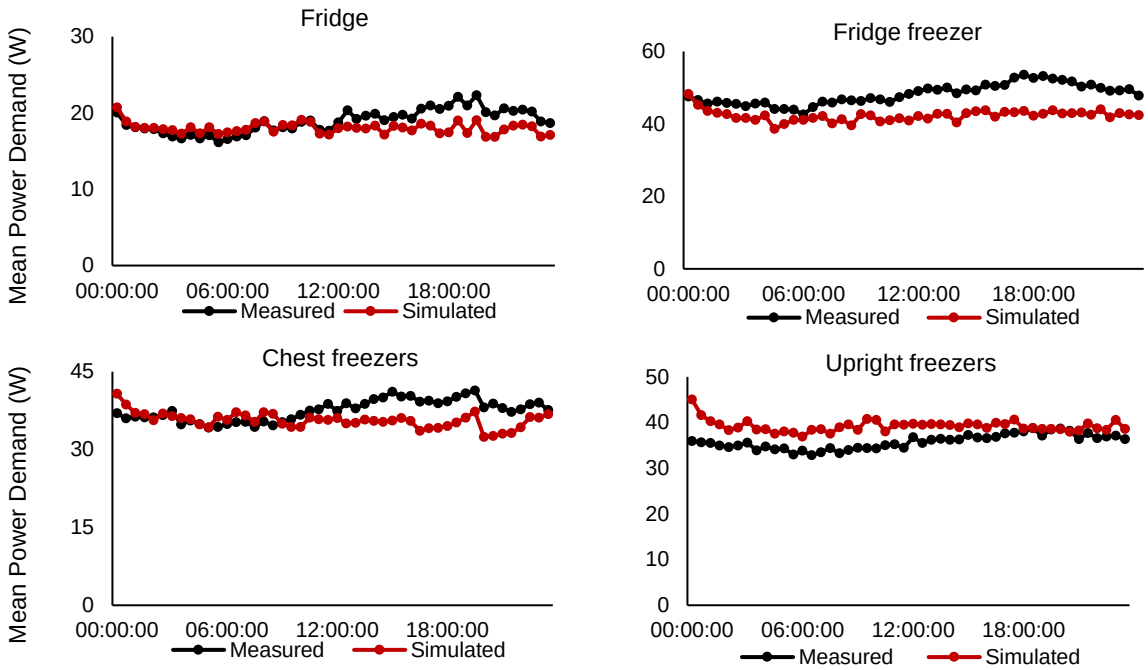


Figure 5.16 Mean half-hourly power demand profiles of cold appliances (The simulated values are calculated using the Approach2_Ind_Hs_Ind_App).

Figure 5.17 presents the mean half-hourly total power demand, percentage errors calculated and box plot of mean of total power demand from 100 simulations of the 16 appliances. The figure of daily power demand of 16 appliance types is calculated by summing up the 16 individual appliances. The percentage errors were calculated same as Figure 5.13. The values calculated here are presented per appliance not per household like other figures presented for individual appliances in this chapter. For example, the mean half-hourly values of washing machines were calculated by taking the mean of 176 washing machines as only 176 washing machines were simulated. It was not divided by 225 (total number of households monitored for 2-minutes) to create average household profiles. The mean diversity profiles do comparatively well in predicting the mean power demand of 16 appliances. Mean values are between the 90th whiskers of the simulated values. However, it barely ever simulates the maximum measured peak. The mean is almost out of the range during peak power loads due to 13-14 % percentage difference. The percentage error between the predictions are scattered between 12% to 15 %. The difference between the simulated and measured values at peak times are due to discrepancies added from the televisions.

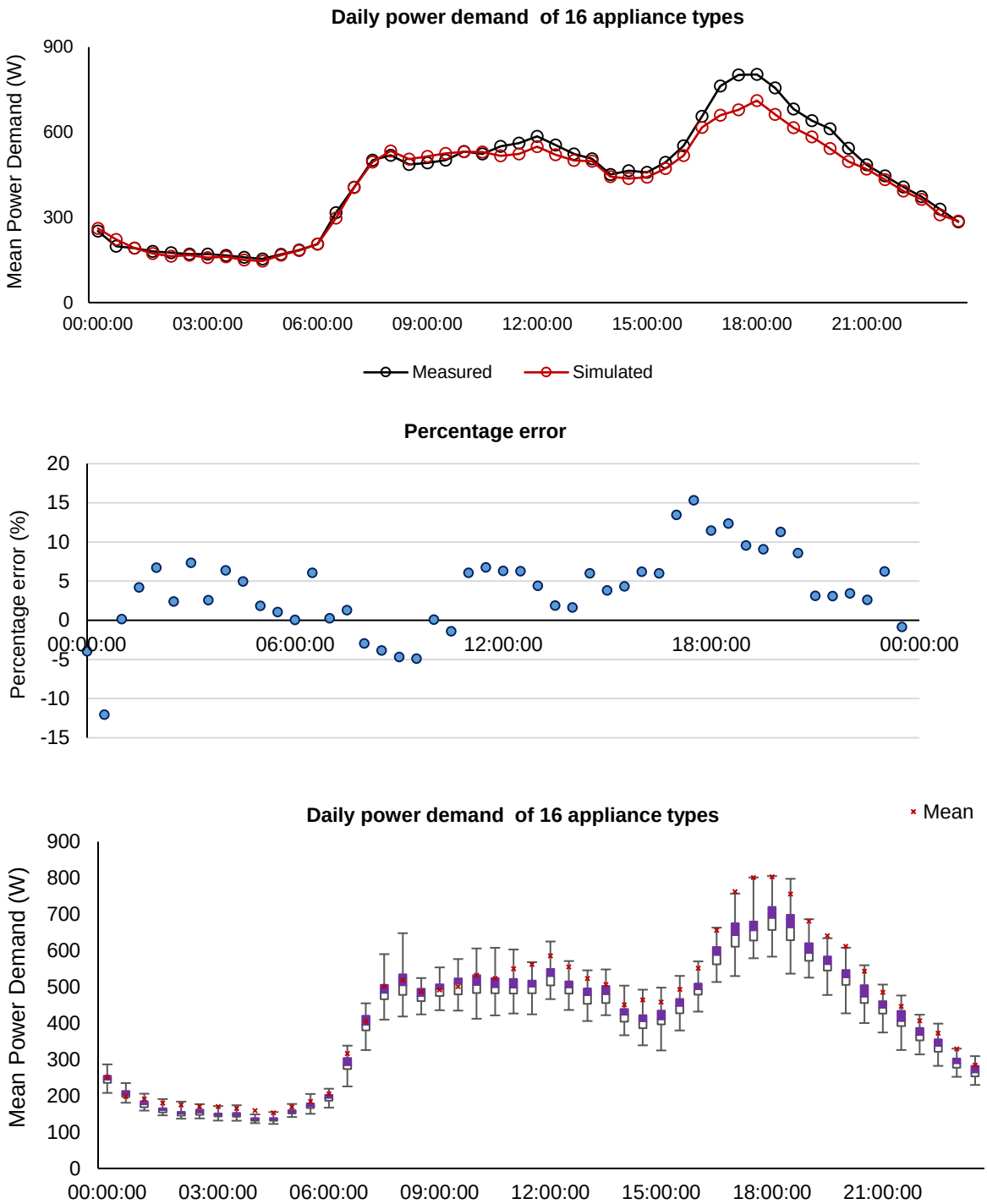


Figure 5.17 Mean half-hourly of total power demand profiles, percentage error and box plot of mean half-hourly of total power demand profiles from 100 simulations of the 16 appliances

5.3.2 Exploration of the reasons of under prediction of peak loads

Chapter 4 concludes that HAU model predicts the three metrics; number of switch-on events, switch-on times and durations of the usage close to the measured values. However, several problems may arise when converting the HAU model to power demand profiles. Figure 5.18 raises an important issue about the time dependency of an appliance run. The significant tests presented in Section 4.4 show that for cooking appliances and televisions there is a significant difference between the durations of appliance use which are switched-on in different times of the day. When the duration and power demand are assigned according to the time-slot when the appliance is switched-on, the HAU model is better at predicting the peak power and daily power demand profiles than the model in which duration and power demand are assigned randomly without considering the time-slot when the appliance is switched-on. This issue was not noticed when comparing the half hourly (30 minutes) probability of switching on profiles for cooking appliances and televisions (Figure 4.12) as the difference between the simulation and measured value was not very significant (up to 4%). Household appliance power demand modelled by assigning durations and power demand considering the time slot the appliance switched-on improved the model predictions (percentage error less than 8%) than the predictions not considered the time dependency (percentage error up to 50%).

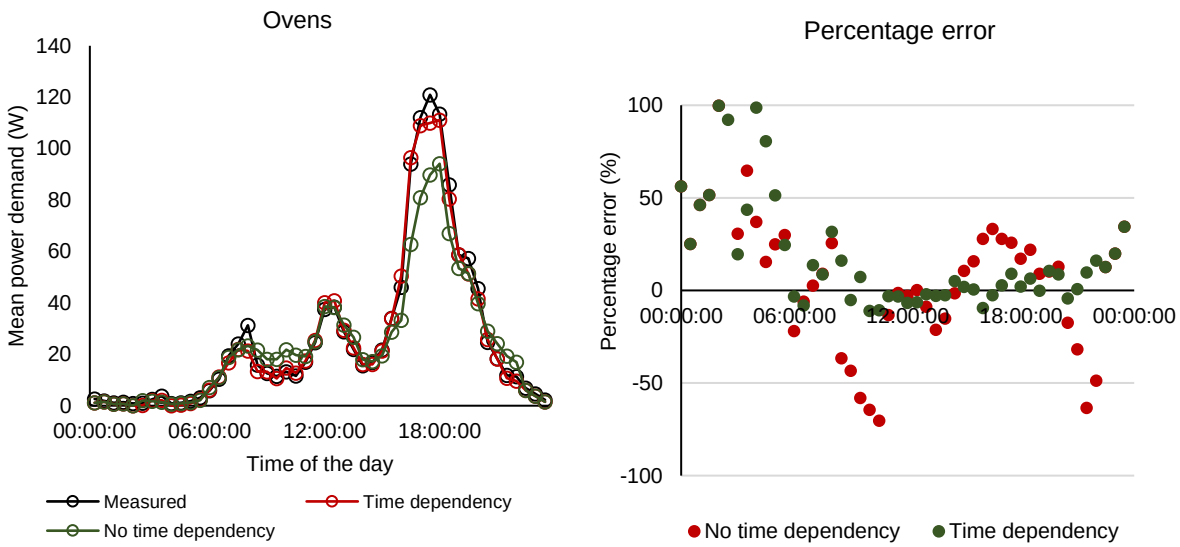


Figure 5.18 Mean half-hourly power demand profiles of oven modelled with and without time-dependency and percentage error plot of the power demand profile.

However, this is not a conclusion for all appliances. The electric showers, cold appliances and wet appliances, time dependency was not considered as the duration and programme choices do not depend on the time slot that the appliance is switched-on. Several studies in literature did not consider this issue (Paatero and Lund, 2006; Richardson et al. 2011) by assigning fixed durations regardless of the time slot the appliance is switched-on. Wilke (2013) considered this issue, and developed distribution of durations depending on the time slot the appliance is switched-on.

5.4 CHAPTER 5: SUMMARY

This chapter has presented the calculation of the electricity consumption trends, appliance characteristics regarding the power demand from the HES dataset and the comparison of the simulation results of the household daily appliance power demand profiles with the measured data for each appliance type modelled and total. This chapter provides important insight to power demand modelling. The results of this chapter is concluded as such:

- The HES dataset shows that there is a significant variation in the average electricity consumption per day households (Table 5.1).
- There is a further variation in power demand of appliances across different time of the day for all 16 appliance types (Figure 5.3).
- The results of the analysis show that for wet appliances and cooking appliances power demand significantly changes during the appliance use. Wet appliances follow a cycle demanding different power during different stages of use (Figure 5.4). Cooking appliances and electric showers have different power levels which fluctuate during the use of the appliance (Figure 5.6). Televisions and cold appliances have mostly constant power though it fluctuates during the use of the appliance and when the compressor is on, respectively. (Figure 5.8 and Figure 5.10).
- Analysis of the appliance characteristics regarding the power demand shows that programme of choice is as important as the other metrics for wet appliances, cooking appliances and electric showers. Though same duration

can be used for another usage, the power demand during appliance use is different to each other (Figure 5.5, Figure 5.7 and Figure 5.9). For TVs and cold appliances, power demand is identical to each appliance use and compressor run (Figure 5.9 and Figure 5.11).

- Power demand profiles per day of appliances were predicted close to the measured values for 16 appliance types. However, peak values were underestimated up to 12 % for most of the appliances.
- The simulation results show that for appliances with long durations of appliance use such as TVs, peak values were not predicted as well as the other appliances (Figure 5.15).
- Durations of appliance which have time-dependency (Figure 4.16), should be modelled as the duration and power demand should be assigned depending on the time-slot the appliance is switched-on so as not to underestimate the peak power (Figure 5.18). However, for televisions which has the longest duration length there are still discrepancies.

6 RESULT #3: APPLICATION OF THE HAU MODEL FOR DEMAND RESPONSE POTENTIAL

6.1 OVERVIEW

This chapter shows the simulation results of the final HAU model and applies demand response where the flexibility of the power demand of the households is assessed. In Section 6.2, three methods that were explained in Section 3.5.5 are tested here to check which method gives the best result for modelling the appliance ownership. Appliance ownership of 13,276 households is modelled by applying the methods developed for appliance ownership model (see Section 3.5.5). 100 simulations were run to generate the results for Method 1, Method 2 and Method 3. The performance of the model is validated through a comparison analysis where the saturation levels (the percentage of the households who have the particular appliance) and the combination of the appliance sets of the simulation are compared with the measured 2011 EFUS data. In Section 6.3, the comparison of the HAU model with external datasets is presented. Yearly electricity consumption of each individual appliance is compared with the values of ECUK Data Tables (BEIS, 2016). Simulation results of the power demand profiles (variation over time of the day) are compared with average daily profiles calculated by the smart meter data of Elexon. In Section 6.4, the developed HAU model is used to apply demand response using the method explained in Section 3.7 where the flexibility of the power demand of the households are assessed by shifting appliances. Implications for households and policy makers are listed.

6.2 RESULTS AND VALIDATION OF THE APPLIANCE OWNERSHIP: SIMULATED VALUES VS. EFUS DATASET

6.2.1 Establishing linking variables for Method 1, Method 2 and Method 3

It is important to state again that the linking variable to Method 1, Method 2 and Method 3 is only tenure type (see Section 3.3.4). It was the only household

characteristics that links the 2013-2014 EHS and 2011 EFUS datasets and is used to allocate the appliances according to a household characteristic rather than randomly allocating. Table 6.1 shows the number of households found in the EHS and the unique appliance sets for different tenure types that is used in Method 1. For example, 210 unique appliance sets found in 2011 EFUS dataset means there are 210 different combinations of 11 appliances for the households which are “own it outright”. Other limitation of Method 1 is that only 11 appliance types can be allocated as it is the number of appliances covered in the 2011 EFUS project which are washing machines, washing-drying machines, tumble dryers, dishwashers, fridges, fridge-freezers, freezers, ovens, hobs, grill and televisions. Fridges are classified into two which are fridges with ice-box and fridges-without ice-box. Therefore, other appliances covered in other datasets such as computers; electric shower etc. cannot be included in the appliance set to form a probability density function from these groups of appliance set. They should be added separately.

Table 6.1 Linking variable of the 2011 EFUS and EHS 2013-2014, number of people for each composition and unique appliance set found for each composition

Tenure composition	Number of households in the EHS dataset	Number of households in the EFUS dataset	Unique Appliance set found in EFUS dataset
Own it outright	4,004	798	210
Buying it with the help of a mortgage or loan	3,683	688	174
Pay part rent and part mortgage (shared ownership)	82	15	13
Rent it	5,387	1,090	182
Live here-rent free	120	25	20
Total number	13,276	2,616	340

Table 6.2 shows the breakdown of the appliance saturation levels across different tenure types for Method 2 and Method 3. There appliance saturation levels are used as an input for Method 2 and Method 3 (see Section 3.5.5).

Table 6.2 The saturation levels (the percentage of the households who have the particular appliance) calculated from the 2011 EFUS dataset for each tenure type

Appliance types	Tenure type				
	Own it outright	Buying it with the help of a mortgage or loan	Pay part rent and part mortgage (shared ownership)	Rent it	Live here-rent free
Washing machine	85%	85%	73%	83%	80%
Washing-drying machines	14%	14%	27%	10%	12%
Tumble dryer	53%	57%	40%	42%	32%
Dishwasher	51%	59%	40%	14%	28%
Separate fridge with ice-box freezer	22%	15%	7%	19%	16%
Separate fridge w/out ice-box freezer	38%	30%	13%	18%	20%
Separate Freezers	61%	49%	13%	34%	44%
Fridge-freezers	57%	70%	80%	69%	72%
Electrical hob	93%	93%	100%	94%	84%
Electrical oven	69%	71%	80%	59%	48%
Electrical grill	59%	63%	67%	52%	36%

6.2.2 Establishing dependencies for all 11 appliance types for Method 3

Method 3 assigns appliances individually with some dependencies (ownership of a tumble dryer depends on the ownership of a washing machine) linking the appliances individually and dependently. New tables are created to show the dependencies of some of the appliances among each other using equations 3.3 to equation 3.7 presented in Section 3.5.5. In this study, the dependencies of two appliances are considered which are washing-drying machine and tumble dryer.

Table 6.3 shows the dependency conditions in which the probability of availability of a washing-drying machine is calculated depending on the availability of the washing machine used in Method 3. The formula for calculating the probability of availability of washing-drying machines for Condition 1 and Condition 2 are given in equation 3.3 and 3.4, respectively. The results show that only 0.8% of the households have washing-drying machine if they already have a washing machine and 75% of the households have a washing-drying machine if there is no washing machine in the house.

Table 6.3 Dependency of having washing-drying machine on washing machine

Condition	Is there a washing machine	Probability of having a washing-drying machine in that household
Condition 1	Yes	0.8%
Condition 2	No	75%

Similar rules have been applied to tumble dryers, however having dependencies on two appliances; washing machines, washing-drying machines. Table 6.4 shows the dependency conditions in which the probability of availability of a tumble dryer is calculated depending on the availability of the washing machines and washing-drying machines used in Method 3. The formula for calculating the probability of availability of washing-drying machines for Condition 1, Condition 2, Condition 3 and Condition 4 are given in equation 3.5, 3.6, 3.7 and 3.8, respectively. The results show that only 5% of the households have tumble dryers if there is no washing machine and washing-drying machine in the house (Condition 1). The results show that 57% of the households have tumble dryers if there is only a washing machine in the house (Condition 3). It shows that having a washing-drying machine in the house, there is a lower probability that the household has a tumble dryer (see the difference between Condition 3 and Condition 4). Whereas, if a household owns a washing machine, there is a higher probability that there is a tumble dryer in the household (see the difference between Condition 1 and Condition 3). Finally, the probability of having a tumble dryer is the lowest if there is neither a washing machine nor a washing-drying machine (Condition 1).

Table 6.4 Dependency of having washing-drying machine on washing machine

Condition	Is there a washing machine	Is there a washing drying machine	Probability of having a washing tumble dryer in that household
Condition 1	No	No	5 %
Condition 2	No	Yes	7 %
Condition 3	Yes	No	57 %
Condition 4	Yes	Yes	36%

6.2.3 Comparison of Method 1, Method 2 and Method 3

Table 6.5 compares the overall appliance saturation levels for the three methods with the measured values from the 2011 EFUS. Models were run 100 times and the simulation results have been generated by taking the average values of 100 simulation runs. Overall saturation levels are compared and shown in Table 6.5 and Figure 6.1. The results have shown that all three methods are good at capturing the saturation levels of the appliances individually.

Table 6.5 Comparison of the appliance ownership saturation levels simulated by the Method 1, 2 and 3 with the measured values from the 2011 EFUS dataset.

Appliance category	Appliances	Measured	Simulated		
		2011 EFUS dataset	**Method 1**	**Method 2**	**Method 3**
Wet appliances	Washing machine	0.84	0.84	0.84	0.84
	Washing-drying machine	0.13	0.13	0.13	0.13
	Tumble dryer	0.49	0.49	0.49	0.49
	Dishwasher	0.37	0.38	0.38	0.38
Cold appliances	Fridge-freezer	0.66	0.66	0.66	0.66
	Separate fridge with ice box	0.19	0.18	0.18	0.18
	Separate fridge without ice box	0.27	0.27	0.27	0.27
	Separate freezer	0.46	0.46	0.46	0.46
Cooking appliances	Electric Oven	0.65	0.66	0.66	0.66
	Electric Hob	0.37	0.37	0.37	0.37
	Electric Grill	0.57	0.57	0.57	0.57
Televisions	Televisions*	2.32	2.33	2.33	2.33

*For televisions, this value is average of number of TVs found in the households.

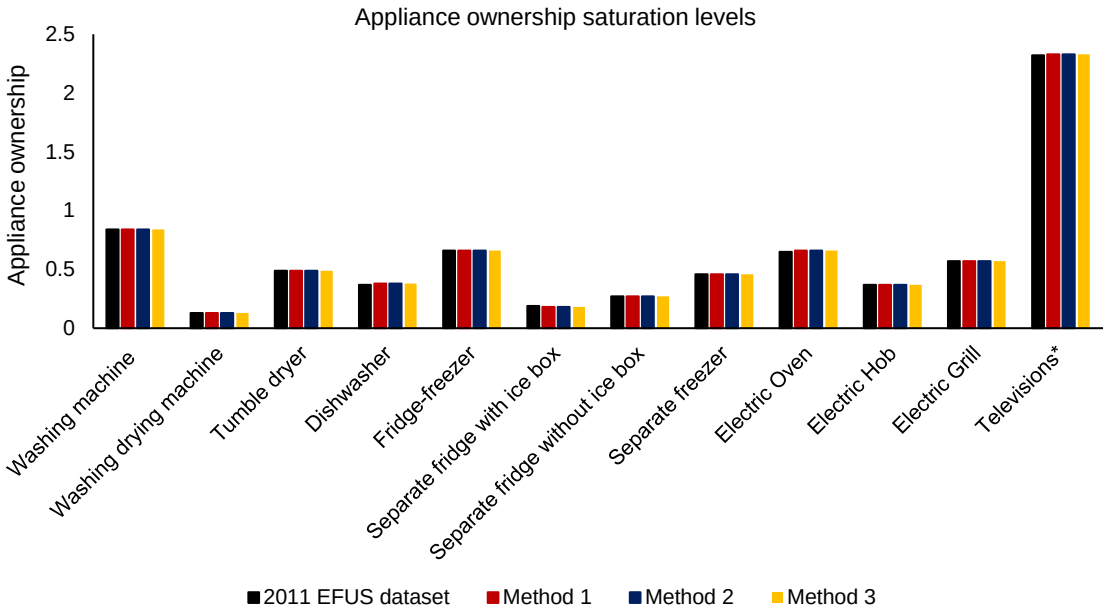


Figure 6.1 Comparison of the appliance ownership saturation levels simulated by the Method 1, 2 and 3 with the measured values from the 2011 EFUS dataset.

6.2.4 Analysis of Dependency: Results of the Method 1, Method 2 and Method 3

This section presents the analysis of dependency of appliances and compares Method 1, Method 2 and Method 3 with the 2011 EFUS dataset in terms of the conditions presented in Table 6.3 and Table 6.4 to test which method does better.

Model has been run 100 times and average results of 100 simulations of these three methods are compared with the 2011 EFUS values. It is important to remind that all three methods were successful at predicting the overall saturation levels (Table 6.5 and Figure 6.1). Firstly, Table 6.6 tests the dependency of the washing-drying machine on the washing machines and compares the saturation levels for the conditions explained in Figure 3.14.

Table 6.6 shows that only 0.8 % of the households with washing machine also have washing-drying machines. Method 1 and Method 3 were good at predicting this dependency however, Method 2 overestimates the percentage of washing-drying machines within the households with washing machines by 4% which is only 0.8% in the measured 2011 EFUS data (see Condition 2). Moreover, it underestimates the saturation levels for washing-drying machines when there is no washing machine (see Condition 1). This is due to the fact that Method 2 assigns the appliances individually without depending on the saturation of the other appliances in this case washing machine. Method 2 fails to populate the set of appliances correctly, allocating more washing dryers to the households.

Table 6.6 Comparison of the saturation levels of the EFUS 2011, simulated values by Method 2 and Method 3.

		Saturation levels of the ownership of the washing-drying machines in those households			
Conditions	**Is there a washing machine in the household**	**EFUS**	**Method 1**	**Method 2**	**Method 3**
Condition 1	No	75	75	14	75
Condition 2	Yes	0.8	0.8	4	0.8

Secondly, Table 6.7 compares the saturation levels for the cases prepared for testing the dependency of the tumble dryers on the washing-drying machine and the washing machines. The results show that only 5% of the households without washing machines or washing-drying machines have tumble dryers in the EFUS dataset. However, Method 2 overestimated this value and predicted the saturation level such as 13%. It overestimated the saturation levels of tumble dryers for Condition 2 whereas underestimated the saturation levels for Condition 3. Method 2 fails to populate the set of appliances correctly, allocating more tumble dryers to those have washing-drying machines and have washing machines and washing-drying machines together.

Table 6.7 Comparison of the appliance ownership of the appliances (saturation levels) of the EFUS 2011, simulated values by Method 1, Method 2 and Method 3.

			Percentage of the Ownership of the Tumble Dryer in those households			
Conditions	**Is there a washing machine**	**Is there a washing drying machine**	**EFUS**	**Method 1**	**Method 2**	**Method 3**
Condition 1	No	No	5%	5%	13%	5%
Condition 2	No	Yes	7%	7%	20%	7%
Condition 3	Yes	No	57%	57%	45%	57%
Condition 4	Yes	Yes	36%	36%	41%	36%

6.2.5 Analysis of combination of appliances: Results of the Method 1, Method 2 and Method 3.

This section presents the comparison of Method 1 and Method 3 in order to find out which method models the combination of appliances i.e. appliance sets correctly. Table 6.5 shows that the saturation levels are predicted correctly by all three methods. Table 6.8 presents the comparison of the number of unique appliances calculated for 13,276 of households which are randomly populated by using Method 1, Method 2 and Method 3 with the measured 2011 EFUS dataset. 13,276 households are randomly populated for 100 simulations. The results given here are the total number of unique appliance sets from 100 simulations. As expected, Method 1 does not pass the number of unique appliance sets found in the 2011 EFUS dataset as the method assigns the appliance sets rather than assigning the appliances individually. However, the unique appliance sets found in the 100 simulations modelled by using Method 2 and Method 3 are far more than the 2011 EFUS dataset. Although some dependencies are considered between several appliance types in Method 3, assigning the appliance types independently from other appliance categories formed more combinations than Method 1 that assigns the appliance sets.

Table 6.8 Comparison of the number of unique appliance sets found by modelling appliance ownership with Method 1, Method 2 and the 2011 EFUS dataset.

	Unique appliance sets found from 100 simulations
2011 EFUS dataset	340
Method 1	332
Method 2	5409
Method 3	5108

6.2.6 Conclusions for the appliance ownership model

According to the results produced and the comparison of the methods with the 2011 EFUS dataset, this conclusion is made. Method 1 and Method 3 should be used together. The reasoning for this decision are:

1- Method 2 fails to capture the inter-dependency of several appliances such as washing machines and tumble dryers and/or washing machines and washing drying machines. (evidence on Table 6.6 and Table 6.7)
2- Method 1 correctly assigns the appliance combination better than Method 2 and Method 3 in line with the EFUS dataset. More combinations were created by Method 2 and Method 3 as the appliances are assigned individually.
3- The disadvantage of Method 1 is that only 11 appliance types in total can be assigned, however the model has to have the capability to be extended to include future technologies and appliance ownership to work on demand response and change of appliance efficiency. Therefore, Method 3 should be included in the model to provide this flexibility.

Considering the conclusions, when modelling the appliance ownership, Method 1 will be used for modelling the 11 appliance types in Table 3.11, and then other appliance types are added such as electric showers and cookers using the Method 3.

6.3 COMPARING THE RESULTS WITH NATIONAL STATISTICS

The HAU (Household Appliance Usage) model generates aggregate electricity demand profiles of 13,276 households that were randomly populated with appliances for 16 appliance types using the procedure described in Figure 3.13. This section shows comparison of the simulation results with external data regarding the electricity consumption and daily power demand profiles.

There are several limitations to do the comparison of the HAU model with external data. First limitation is due to different data resources. For example, the HAU model uses the nationally representative 2011 EFUS dataset to model the appliance ownership. Therefore, it is not possible to compare the aggregate power demand of

the HAU model with measured aggregate electricity demand profiles of the 2011 HES dataset as the number of appliances and types are different from each other. To give an example, the appliance saturation level of electric ovens is 20% in the HES dataset whereas it is 65% in the 2011 EFUS dataset. Obviously, in the HAU model, the total aggregate power demand of ovens is overestimated when compared to the measured values of 2011 HES dataset. Therefore, it is difficult to compare the total aggregate power demand profiles of appliances in the UK residential sector. Secondly, the HAU model generates only the household electricity demand profiles. However National Grid presents only the total daily electricity demand profiles and the electricity demand solely from the residential sector is unknown. Therefore, the HAU model cannot be compared to the results of the National Grid. Thirdly, the HAU model generates electricity demand profiles only for 16 appliances types. However, there are limited studies that present power demand profiles on an individual appliance level to compare with.

To do the comparison of the HAU model with the national statistics, the results of aggregate electricity demand profiles of 13,276 households generated by the HAU model is scaled up to national level. The weighting factors calculated by the 2013-2014 EHS study are used to scale up the number of households hence the electricity demand consumption.

Considering the limitations, only the electricity consumptions of appliances are compared. The average results are compared with the study of “Energy Consumption in the United Kingdom (ECUK)”. ECUK is an annual statistical publication that provides a comprehensive review of energy consumption and changes in efficiency, intensity and output since the 1970s, with a particular focus on trends since 2000 (BEIS, 2016). The calculations done for electricity consumption of appliances shown in the ECUK Data Tables (mainly Table 3.02 and Table 3.08) were used to compare the electricity consumption of the appliances of the HAU model. Different dataset and modelling techniques are used for calculating the energy use of the appliances in different Data Tables of the ECUK study. Therefore, the report indicates that there are some small discrepancies between the totals for cooking and appliances in different Data Tables due to differences in the methodologies used and the items included in each figure.

Table 6.9 explains the datasets and modelling techniques used in the ECUK study in more details along with the HAU model.

Table 6.9 Description of the study of ECUK that used to compare the HAU model

Study	Datasets used for modelling	How modelling is done?
ECUK Data Tables (Table 3.02 and Table 3.08)	-Cambridge Housing Model (CHM) (DECC,2015) -Market Transformation Programme (MTP) (DEFRA,2011)	The publication provides two outputs of domestic energy consumption split by end-use both of which provide information on lighting, cooking and appliance energy use. Table 3.02 gives total energy use by fuel type by general end use, based on the outputs of the Cambridge Housing Model (CHM) which estimates lighting, cooking and appliance use using improved SAP algorithms. The primary source of input data for the CHM is currently the English Housing Survey (EHS). In these calculations the number of occupants is taken straight from the input housing data, where it is available, and is used in all relevant calculations. The calculations for determining the energy use for electrical appliances and cooking, which are not explicitly stated in SAP 2009, these calculations are based on BREDEM 8. Table 3.08 gives specific energy use for a range of consumer items, based on data provided by Market Transformation Programme (MTP). from an analysis of the penetration of appliances and lighting into UK homes, e.g. through sales figures.
HAU model	- 2011 EFUS - 2013-2014 EHS - 2011 HES	13,276 households from the 2013-2014 EHS dataset were randomly populated with appliances using the 2011 EFUS dataset. Then the HAU (Household Appliance Usage) model generates aggregate electricity demand profiles of 13,276 households that for 16 appliance types using appliance electricity profiles derived from the 2011 HES dataset.

The number of appliances studies are limited and only those that are common with the HAU model could be compared. Table 6.10 presents the comparison of the yearly electricity consumptions of several appliance types. Since only yearly electricity consumption is available, HAU model is run 100 times for a year to match with the external data. The average of 100 simulations are compared with the ECUK appliance electricity consumption (DECC, ECUK Table 3.9). It is important to note that number of households are different for both studies as ECUK covers United Kingdom whereas HAU model which is based on EHS 2013-2014 covers only England. The numbers were not expected to be the same due to different data sources and modelling techniques. Yearly average electricity consumption per household (kWh) was calculated to compare the HAU model simulation results and ECUK. Total yearly electricity consumptions were not compared as the total number of households are different.

The results show that the yearly average electricity consumptions of washing-drying machines were significantly underestimated by 60%. Both the yearly average electricity consumptions of washing machines and dishwashers were underestimated by 18% and 17%, respectively whereas the yearly average electricity consumptions of tumble dryers were overestimated by 11%. Yearly electricity consumptions of the cold appliances were similar both in ECUK and HAU model. Yearly average electricity consumptions of cooking appliances were overestimated up to 40%.

Table 6.10 Comparison of the electricity consumption of the appliances of the ECUK and HAU model simulations

		ECUK Tables (2014)	HAU model	
Appliance category	**Appliance type**	**Yearly average electricity consumption per household (kWh)**		**Percentages**
Wet appliances	Washing Machines	168.3	138.4	-22
	Washing-drying machines	87.5	35.4	-147
	Tumble dryers	175.3	198.4	12
	Dishwashers	121.6	101.4	-20
	Total	552.7	473.9	-17
Cooking appliances	Electric Oven	114.6	146.6	22
	Electric Hob	118.7	198.0	40
	Total	233.3	344.6	32
Televisions		260.4	299.1	13
Cold appliances	Fridges	63.2	75.3	16
	Fridge-freezers	260.5	281.2	7
	Freezers	119.1	148.8	20
	Total	442.8	505.3	12

One of the criticisms of the HES dataset, which is used for appliance behaviour modelling, is that this dataset is not nationally representative. In addition, all of the households in the HES were owner-occupied; therefore, the electrical appliance usage may not be representative of the UK. This is due to appliance ownership rate and occupancy patterns can differ between different households. More representative data of appliance usage could improve this results.

Secondly, power demand profiles per household in an average day predicted by the simulations of the HAU model and the dataset of Elexon are compared (Figure 6.2). The average total power demand profiles per household calculated from the HES dataset is also included in the Figure 6.2. HAU model was compared to the line graph which was drawn using data from Elexon Ltd data archive for 2013-2014 (Elexon, 2016). The power demand profile in an average day is created by recording

and analysing half-hourly demand data of 384 households from a representative sample of customers which are randomly selected within each Grid Supply Point (GSP) Group (a collection of GSPs for a region) during one year in 1997. The data used here have the values for 2013-1014 where the values for half-hourly readings were adapted to 2013-2014 using regression.

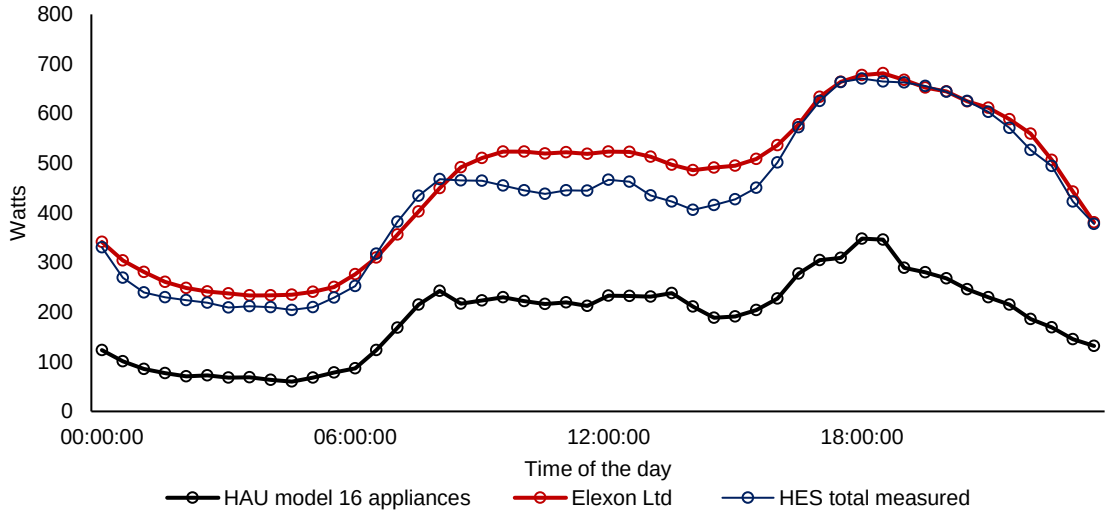


Figure 6.2 Comparison of the power demand profiles per household in an average day of the HAU model, HES total measured values and the Elexon Ltd. dataset

Figure 6.2 shows that the shape of the daily power demand profiles per household in an average day of predicted by the HAU model was similar to that of Elexon. However, the evening peak period was longer for the Elexon data than predicted by the HAU model. This could be because ICT and audio-visuals except for TVs were not modelled. It is important to note that HAU model only simulates 16 appliance types (calculated using the HES dataset). This could explain the values that were underestimated during the evening peak and during the night. If lighting, all audio-visuals and ICT such as sky-box, play-stations etc. and the rest of the appliances which DECC report labelled as unknown (see Figure 1.1) are modelled, the gap between the total power demand profiles and 16 appliance types can be closed. However, individual appliances that belong to this category are too small to be modelled individually but can be collectively significant. It can be suggested that the power demand profiles of these appliances can be stochastically modelled as a bulk, however this study focused more on individual appliance modelling and chose the

appliances which contributed the most to the total demand, peak demand and suitable for demand response.

6.4 APPLICATION OF THE HAU MODEL FOR DEMAND RESPONSE MODELLING

6.4.1 Overview

This section presents the modelling of demand response using the HAU model. Because demand-shifting takes place through the individual scheduling of household appliances, the focus lies on the appliances level. Each household owns appliances, which build-up the electricity demand of the household. Appliances are shifted to reduce the peak loads in the network by shifting loads from peak periods to off-peak periods (lower demand time slots). Lower demand time slots refer to the periods that are lower than the average demand. To assess the potential of this demand-shifting, the HAU model was used to simulate the electricity demand profiles using different scheduling schemes. The national evening peak was assumed to be between 17:00 and 20:30. The demand response model allows the user to change the determined peak times. Appliances in this time slot will be shifted to after 9pm until midnight. Similarly, the time slot can be determined as a different slot and the model gives this flexibility to change the input of peak times and off-peak times. Several assumptions were made before running the demand response cases:

Assumption 1: Demand response is applied only to the households who had a switch-on event of the appliance for that particular day. In other words, demand response is not considered if the washing machine was not switched-on at all in that particular day. In practical terms, this assumption is made to ensure not to create extra switch-on events for households who did not use the appliance in that particular day.

Assumption 2: If there is a switch-on event of the appliance in the off-peak time, the appliance in the on-peak time is not shifted to the off-peak time. For example, if there are two switch-on events of dishwasher; first one 18:30 and the other at 21:30, the dishwasher at 18:30 is not shifted to the off peak time. Having switch-on events

during off-peak time, shifting the appliances to off-peak time would overlap with the uses of appliance at off-peak times. Considering this issue in practical terms, this assumption is made to ensure not to change the total number of switch-on events during that particular day.

6.4.2 Demand shifting of the electrical appliances

Seven appliances are focused in this section and five demand response cases were applied. Wet appliances from the time-shiftable appliances (washing machines, washing-drying machines, tumble dryers and dishwashers) and cooking appliances (ovens, hobs and grills) are chosen to apply the demand response cases. Daily electricity demand profiles of 13,276 homes with 16 appliance types are simulated using the HAU model. Table 6.11 presents the parameters designed for the demand response cases applied to the simulated daily electricity demand profiles of 13,276 homes. Households with both washing machines and tumble dryers are not considered in the cases to see the effect of demand shifting of individual appliances. For this reason, demand response is only applied to households with only washing machines in which the switch-on event of the washing machine is shifted to a later time of the evening. This cannot be performed for households with both washing machines and tumble dryers as the order of these appliances are changed which in reality that is be possible (tumble dryer almost always works after the washing machine). In those cases, shifting of both washing machine and tumble dryer should be considered.

Table 6.11 Parameters of the simulated demand response cases

	Probability of households willing to shift to a lower power demand					
	Washing machine (only)	Washing-drying machine	Tumble dryer	Dishwasher	Ovens	Grills
Case 1 (no change)	0%	0%	0%	0%	0%	0%
Case 2	20%	20%	20%	20%	20%	20%
Case 3	40%	40%	40%	40%	40%	40%
Case 4	60%	60%	60%	60%	60%	60%
Case 5	80%	80%	80%	80%	80%	80%
Case 6 (every household shifts)	100%	100%	100%	100%	100%	100%

Table 6.12 presents the effects of demand shifting of wet appliances and cooking appliances on the household power demand. The results of Case 6, which the percentage of the households willing to shift to a lower power demand is 100%, is shown as an example in Table 6.12. Case 6 is chosen to show the maximum decrease and extent of flexibility that can be provided. The simulations are run using the methods described in Section 3.7. It is important to note that 13,276 homes with appliances are generated for one day and 1 run consists of modelling the electricity demand profiles and applying the demand response for a certain scenario. The mean simulation results of 100 simulations from 13,276 households were scaled up to 22.6 million English homes using the weighting factors calculated by the 2013-2014 EHS study.

Firstly, the number of switch-on events during the peak period (17:00 to 20:30) was calculated. Ovens have the highest average number of switch-on events during the peak periods per household (0.22) whereas washing-drying machines have the lowest average number of switch-on events per household during the peak periods (0.02). This is partly due to appliance ownership of the 13,276 households. 12.7% of the 13,276 households have washing-drying machines whereas 65.5% of the 13,276 households have ovens. The appliance ownership is not the only factor on the number of switch-on events during peak period. Switch-on daily profiles of appliance are also important. For instance, number of switch-on events of ovens is twice as many as for washing-drying machines in the evening peak (see Figure 4.4). The effect of the second assumption can be seen at the percentage of number of switch-on events shifted from the peak power. For example, grills have the highest percentage of number of switch-on events shifted from the peak period (100%). This is due to the fact that there are more free places at off-peak period (21:00 to 00:00) to shift the usage of grills than rest of the appliances. There is almost no usage of grills after 21:00 (See Figure 4.4). In other words, due to Assumption 2 (If there is a switch-on event of the appliance in the off-peak time, the appliance on the peak time is not shifted to the off peak time), although there are quite a lot of appliance switch-on events for wet appliances during peak period, because there are still switch-on events at off-peak period, the shifting of the appliances is not done. This caused the percentage of number of switch-on events shifted from the peak period for wet appliances be under 66% although the probability of shifting the appliances to off-peak period is 100%.

The amount of flexible demand available in peak hours is of interest for utilities. The simulation results show that the effects of shifting appliances are different for the same demand response case. Ovens have the highest absolute decrease of the electricity consumption from the peak period (2046.1 MWh) for the national scale and have the highest absolute decrease of average power demand from the average peak demand (decrease of 56.7 Watts from the highest peak power demand) per household. Although total power demand of the household was not simulated (only 16 appliance types were simulated with the HAU model), 56.7 Watt decrease corresponds to 8.4% decrease from the total load calculated from the HES dataset shown in Figure 6.2. This may be due to the high oven saturation levels (65%) and the number of switch-on events of ovens during the evening peak period. In addition, average power demand per usage is high too. Grills and washing-drying machines have the lowest absolute decrease of the electricity consumption from the peak period (2064.1 MWh) for the national scale are 109.8 MWh and 137.8 MWh, respectively. The electricity consumption during each usage is very important. This effect can be seen when the decrease of total electricity demand from the peak demand per number of shifted appliances (Wh/appliance) is analysed. For example, although the absolute decrease of the electricity consumption from the peak period (2064.1 MWh absolute decrease of the electricity consumption from the peak period for the national scale) of ovens is the highest compared to the other appliances, decrease of total electricity demand from the peak demand per shifted appliance (511 Wh) is lower than dishwashers and tumble dryers which are 1136.5 Wh and 1276.2 Wh. Average power demand of tumble dryers and dishwashers for each usage is higher than those of ovens, washing machines and washing-drying machines which leads to higher decrease of total electricity demand from the peak demand per number of shifted appliances. This result could be an important indicator for individual households as it shows that shifting tumble dryers and dishwashers have more effect than on their electricity demand during peak hours.

Table 6.12 Results of mean of 100 simulations of 13,276 households for Case 6 (100% of the households agreeing to shift to a lower power demand)

Appliance types	Washing machines	Washing-drying machines	Tumble dryers	Dishwashers	Ovens	Grills
Number of switch-on events during the peak period per household[1]	0.085	0.020	0.077	0.067	0.212	0.077
Number of switch-on events shifted from the peak period per household	0.053	0.009	0.047	0.044	0.176	0.077
Percentage of number of switch-on events shifted from the peak period	62.1%	59.1%	62.0%	66.7%	78.9%	100.0%
Absolute decrease of average power demand from the average peak demand (Watts)[2] per household	12.2	1.24	14.8	16.7	56.7	3.4
Percentage decrease of average power demand from the average peak demand[3]	72.9%	35.7%	48.1%	57.0%	75.9%	80%
Absolute decrease of the electricity consumption from the peak period (MWh)[4] for the national scale	994.9	137.8	1316.9	1118.1	2046.1	109.8
Absolute decrease of the electricity consumption from the peak period (kWh) per household	0.044	0.006	0.06	0.05	0.09	0.004
Percentage decrease of the electricity consumption from the peak period[5]	62.3%	45.3%	53.7%	70.0%	55.9%	97.1%
Decrease of total electricity demand from the peak demand per number of shifted appliances (Wh/appliance)[6]	830.2	666.67	1276.4	1136.5	511.2	51.9

[1] Peak period is between 17:00 and 20:30. The average value of the number of switch-on events during peak period of 100 simulations for 13,276 households is scaled up to national level, and then divided by 22.6m homes to give the value per household.

[2] The average peak power is subtracted by the new value at the peak time after the appliance is shifted. For example, for washing machines, the average peak power was 16.6 Watts at 18:30 and for Case 6 the new value at 18:30 is 4.4 Watts, therefore the absolute decrease of average power demand from the average peak demand is 12.2 Watts.

[3] Calculated by dividing the new peak value by the original peak power demand. For washing machines, the percentage decrease of average power demand from the average peak demand is 12.2/16.4=73.5%

[4] It is the difference between the total electricity consumption between 17:00 and 20:30 from 13,276 households and the new total electricity consumption between 17:00 and 20:30 after shifting the appliance (for Case 6). For tumble dryers, the total electricity consumption between 17:00 and 20:30 (2451.65 MWh) is subtracted by the new total electricity consumption between 17:00 pm and 20:30 (1134.7 MWh) which equals to 1316.9 MWh.

[5] Calculated by dividing the new total electricity consumption by the new total electricity consumption between 17:00 and 20:30. For tumble dryers, the percentage decrease of the electricity consumption from the peak period is 1316.9/2451.6=53.7%

[6] Calculated by dividing the absolute decrease of the electricity consumption from the peak period by number of switch-on events shifted from the peak period. For washing machines, the decrease of total electricity demand from the peak demand per number of shifted appliances is 0.044/0.053*1000=830.2Wh.

Figure 6.3 and Figure 6.4 compare the power demand profiles of households equipped with wet appliances (washing machines, washing-drying machines, tumble dryers and dishwashers) and cooking appliances (ovens and grills), respectively where demand response is applied with their original power demand profiles (when shifting did not happen, shown in black line in the figures). The effect of the demand shifting on the individual appliance electricity demand profiles of these appliances for each case is shown. As expected, more the percentage of the households willing to shift their appliances, more sharply the power demand from the peak time decreases. The simulation results also show that additional peaks are created by shifting appliances to a later time. For example, households being involved in shifting the washing machines more than 80% caused exactly the same peak for another time slot. For tumble dryers, households involved in demand shifting more than 60% caused a similar peak in the off-peak time.

Table 6.12 points out that the amount of flexible demand available in peak hours varies for different appliance types. The comparison of different cases in Figure 6.3 and Figure 6.4 also shows that same decrease can be achieved with different appliances for different cases. These comparisons can be useful for policy makers. For example, convincing only 40% of the households to shift their dishwashers or tumble dryers can lead to same decrease for households with ovens where 20% of the households agrees to shift their ovens.

For all the graphs, lines between 01:00 am to 16:30 overlay because there is no change in the power demand therefore all lines are on top of each other. After 16:30 a thick black line is plotted to clearly show the case which represent no demand response

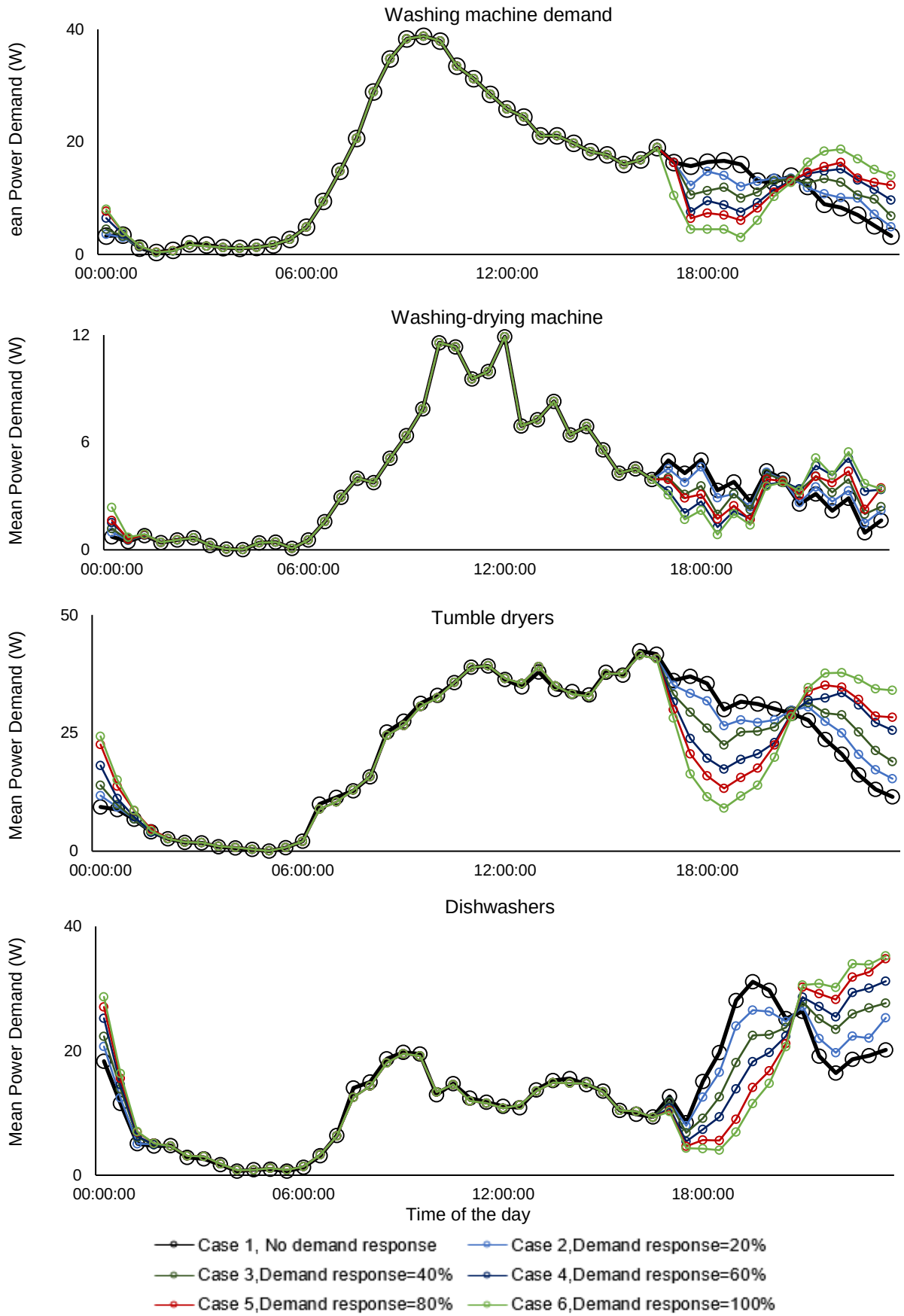


Figure 6.3 Average daily electricity demand profiles of wet appliances per household with difference demand response cases

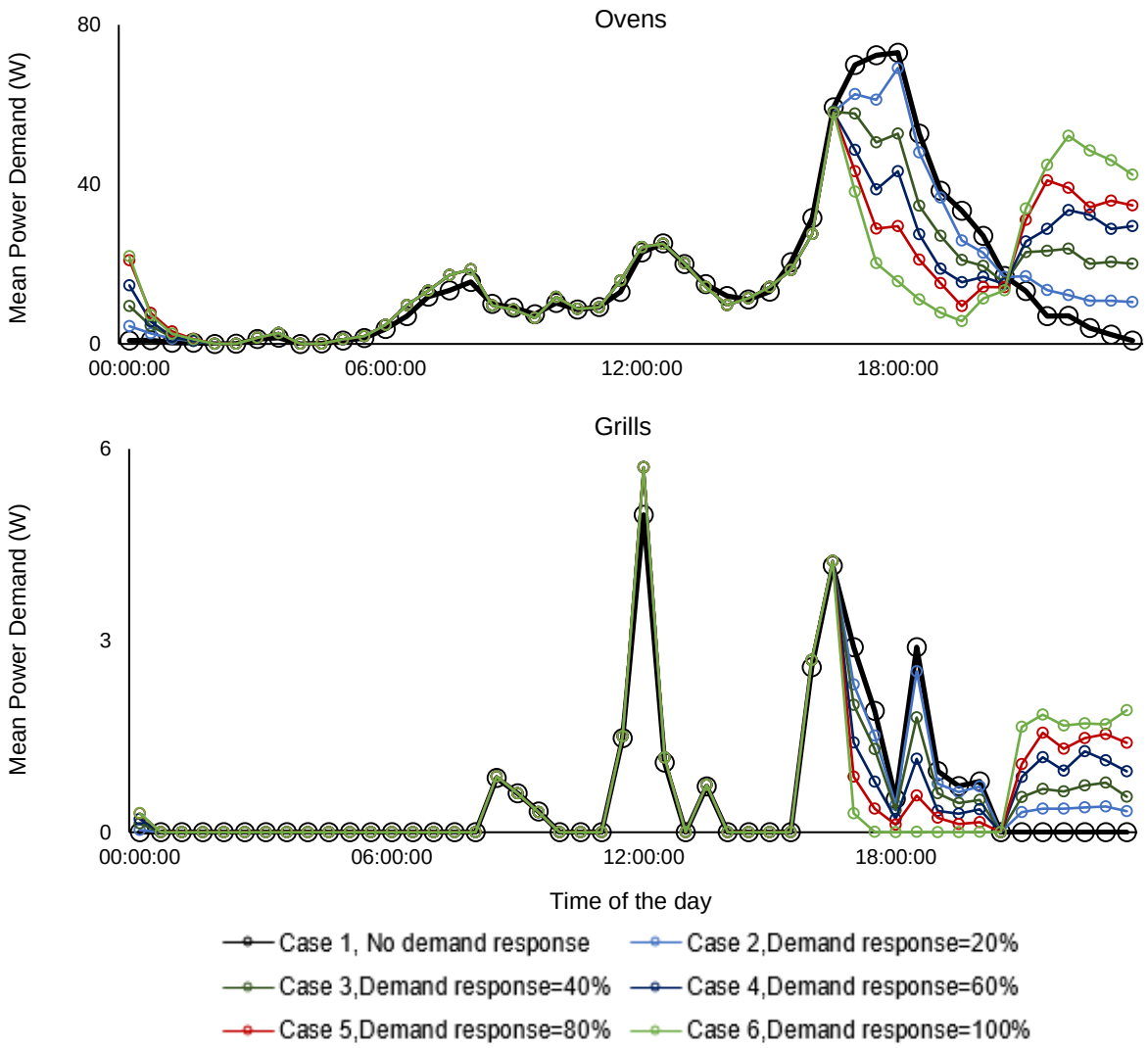


Figure 6.4 Average daily electricity demand profiles of wet appliances with difference demand response cases

6.4.3 Flexibility quantification across household types

The amount of flexible demand available in peak hours for different household types can be of interest for policy makers. In this study, the tenure types were the household characteristics modelled. The reason for this is explained in Section 3.3.4 and the tenure types are shown in Table 6.1.

Table 6.13 shows the absolute decrease of average electricity consumption (kWh) from peak load. Peak load is determined again as from 17:00 to 20:30. Table 6.13 shows the shifting of three appliances which are washing-drying machines, tumble

dryers and dishwashers for Case 6 where the probability of shifting these appliances to a lower demand is 1.0. Average results of 100 simulations are presented.

For all three appliances, the highest absolute decrease of average electricity consumption (kWh) from peak load belongs to households who pay part rent and part mortgage (shared ownership) whereas the lowest absolute decrease of average electricity consumption (kWh) from peak load belongs to households who live there and rent free. The results show that for washing-drying machines, the highest absolute decrease is from the households who pay part rent and part mortgage (shared ownership). Households who own it outright and are buying it with the help of a mortgage or loan have a similar absolute decrease of average electricity consumption (kWh) from peak load when the washing-drying machines are shifted to a later time. Households who own it outright or are buying it with the help of a mortgage or loan have similar absolute decrease of average electricity consumption (kWh) from the peak load. Their values are mostly in between the households who pay part rent and part mortgage (shared ownership) and rent it. The results show that the households who buy the house with the help of a mortgage or loan can be prioritised when targeting customer.

Table 6.13 Comparison of the absolute decrease of average electricity consumption (kWh) from peak load across different tenure types of 100 simulations for case 6

		Absolute decrease of average electricity consumption (kWh) from the peak load[1]				
Appliance category	Appliance type	Own it outright	Buying it with the help of a mortgage or loan	Pay part rent and part mortgage (shared ownership)	Rent it	Live here-rent free
Wet appliances	Washing machines	0.051	0.060	0.043	0.013	0.030
	Washing-drying machines	0.007	0.007	0.015	0.004	0.003
	Tumble dryers	0.055	0.057	0.047	0.043	0.030
	Dishwashers	0.053	0.063	0.044	0.014	0.026
Cooking appliances	Ovens	0.103	0.105	0.107	0.089	0.085
	Grills	0.004	0.004	0.005	0.004	0.20

1 Average electricity demand of appliances are calculated as dividing the total electricity consumption from the appliance during peak load by the number of appliances available in the household.

6.5 CHAPTER 6: SUMMARY

This chapter firstly presents the simulation results and the validation of the appliance ownership model. Secondly, the simulation results of the HAU (Household Appliance Usage) model that generates aggregate electricity demand profiles of 13,276 households that were randomly populated with appliances for 16 appliance types were compared with the Data Table presented by “Energy Consumption in the UK (ECUK)”. Thirdly, the HAU model is used to apply demand response for several scenarios and household types in order to assess the available flexible power demand and quantify the demand response potential in the UK households. The results of this chapter are concluded as such:

- Method 1 will be used to model the 11 appliance types that are available in the 2011 EFUS dataset, other appliances such as electric showers which are not included in 2011 EFUS will be added to the household appliances with Method 3.
- Limitations of the verification of the HAU model are listed as lack of external data to compare the appliances individually. In addition, there are discrepancies due to different data sources and modelling techniques.
- The comparison of the appliance yearly average electricity consumption (kWh) of the HAU model with the ECUK Data Tables shows that HAU model predictions underestimate the values of washing machines and dishwashers up to 18% compared to Data Tables of ECUK whereas the yearly average electricity consumptions of the cooking appliances were overestimated by up to 20%.
- The comparison of the power demand profiles per household at an average day of the HAU model with the HES total measured values and the Elexon Ltd. dataset shows that the shape of the daily power demand profile is similar, however lower than the total values as only 16 appliance types were modelled.
- The predictions of the HAU model of cold appliances were also overestimated up to 11-18% compared to the Data Table of ECUK.
- Simulation results show the amount of flexible demand available during peak load is a combination of appliance ownership and probability of switch-on events during the peak load.

- Shifting the appliances has different effects on the electricity consumption which can provide two different implications which are:

  1) First implication is the total effect of shifting appliances in the network. The simulation results of the demand response show that ovens have the highest absolute decrease of average power demand from the average peak demand (decrease of 56.7 Watts from the highest peak power demand) and absolute decrease of the electricity consumption from the peak period which means they offer the highest amount of flexible demand available in peak compared to the other appliances in the network (Table 6.12). This result could be interesting for utility companies.

  2) Second implication is the individual effect of shifting appliances in the household: Decrease of total electricity demand from the peak demand per shifted appliances was the highest for dishwasher and tumble dryers which are 1136.5 Wh and 1276.4 Wh (Table 6.12). This could be interesting for the households who want to prioritise some appliances over others.

- For all three appliances, the highest absolute decrease of average electricity consumption from peak load belongs to households who pay part rent and part mortgage (shared ownership) whereas the lowest absolute decrease of average electricity consumption from peak load belongs to households who live there and rent free. This could be interesting for policy makers who want to prioritise household types to successfully apply the demand response in the network.

7 DISCUSSION

This thesis has presented the results of an investigation into new approaches to household appliance behaviour modelling to generate realistic electricity demand profiles for domestic appliance use. The approach developed is based on measured data, focuses on appliance and occupant behaviour modelling and converts these into power demand profiles. This discussion chapter brings together findings from the results chapter (Chapter 4-5-6) and jointly discusses their implications, addressing the Research Objectives 2 to 5.

The first three sections focus on the methodologies. The occupant behaviour monitoring and data collection methodologies are firstly discussed (section 7.1), highlighting some limitations. The next section contains a discussion on the occupant behaviour modelling and simulation methodologies (Section 7.2) and methodologies for the assessment of household appliance usage model (Section 7.3). Research Question 1 is dealt with Section 7.2. Then, Section 7.4 discusses the finding of the demand response modelling (and in so doing address Research Question 2) and the possible implications. The discussion is summarised in Section 7.4, with the main conclusions of the study presented in the following chapter (Chapter 8).

7.1 APPLIANCE BEHAVIOUR MONITORING AND DATA COLLECTION METHODOLOGIES

This study has contributed to an improved understanding of the behaviour of household appliance use in the UK homes. A strength of this study, as opposed to previous studies which have relied on diary-based ‘time of use’ datasets, is the use of monitored electrical power demands of individual appliances to develop the high resolution stochastic model. The HES study recorded the power demands of the appliances at 2 minute intervals for monthly monitored households. This dataset brings some advantages compared to the studies that used Time-of-Use data which obtained the switch-on times and duration of appliance use from user diaries and then converted to appliance power demands with fixed power demand profiles. In this approach, the switch-on times cannot be identified precisely as users write down their

daily activities each 10 or 15 minutes. In Section 3.5, it is shown that switch-on and switch-off events of the appliances can be identified on a 2-minute basis from the recordings of power demands of the appliances. Moreover, Section 4.2.3 shows that there are activities which the duration of the appliance use is less than 15 minutes such as electric showers (4 to 8 minutes), televisions (2 to 14 minutes) and hobs (4 to 12 minutes). Therefore, the HES dataset enabled to identify these short activities as opposed to Time of Use studies.

Another limitation of the one-day diary based Time of Use datasets is that they fail to capture the difference in behaviour for an extended period of time and difference in durations/choice of programme between usages. HES dataset had at least a 27 days monitoring period. For example, the analysis of the power demand profiles and average power demand presented in Section 5.9 shows that different power demand profiles were observed for different appliance usage by the same household. This is information that cannot be derived from the Time of Use datasets, therefore the studies such as Richardson et al. (2010), Paatero and Lund (2010), Widén et al. (2012) and Wilke et al. (2013) had to use average power profiles for the appliance usage. A discussion in Section 5.3.2 presents that averaging the power demand (even for televisions) significantly affect the modelling results. They also used the same power demand during each use of appliance. However, the results presented in Section 5.2.2 show that power demand during usage is different for each usage. This is especially significant for wet appliances and cooking appliances in which the choice of programme and power levels for electric cooking varies between usages.

With the monitored data, diversity in appliance behaviour can be identified in the individual households. This is done by creating individual probability density functions (PDF) for switch-on times and cumulative distribution function (CDFs) for number of switch-on events and durations explained in Section 3.5. However, the results obtained are limited by the relatively short monitoring period and small sample size. For instance, the homes were monitored for between 20 and 45 days, with an average monitoring period of 27.7 days, after which the equipment was moved to another household. This was done to minimise the monitoring equipment costs of the survey. As a result, different households with different appliances were monitored in different seasons throughout the monitoring period. This makes it difficult to discern if the variations in the appliance occupant behaviour is due to household characteristics,

seasonal changes or other factors. The lack of recent studies on monitoring of individual appliances is because they are expensive to allocate smart plugs for every individual appliance and households agreeing to have their households monitored are not widely available. As smart and connected homes make monitoring easier and less costly, future surveys could have greater sample sizes and monitor homes in parallel, and for longer time periods. Such longitudinal studies will allow the complex interaction of factors which lead to different behaviours in different household types at different time of year to be better understood.

Attempts were made to differentiate the occupant behaviours based on the number of people living in the home and the household type (i.e. family vs single persons, working-household vs pensioners), controlling for other characteristics. Little consistency across homes with respect to which appliances are metered. e.g. House 1 with 2 occupants might have hob and an electric shower but none of the other homes with 3 or 4 occupants in the dataset have these. Indeed, the HES dataset proved to be too small to perform meaningful statistical comparisons in this case. In chapter 4, it is shown that ANOVA test could not be performed for some appliances to test the variation among the number of occupants or household types as the sample size is small or non-existent. This includes several cooking appliances such as grills (n=5), hobs (n=9) and TV3 (n=21). Splitting the sample into subgroups may also degrade the model's predictive performance due to data scarcity. A much larger future study would be beneficial to improve the representativeness of the survey and to validate the findings of the existing study.

Furthermore, the HES study recorded the power demands of the appliances rather than the actions of individual occupants. Occupant behaviour had to be defined at the household level rather than at the individual level as it was only possible to track when appliances are switched on, not by whom. Other studies that used Time of Use datasets, they have the daily order of activities for individual occupants in the house. Appliance usage patterns by an individual may be inter-correlated and it is not clear from the current analysis if it is possible to generalise this to other appliance correlations as it is not known the order of appliance use by an individual occupant. Because the HES study recorded the power demands of the appliances rather than the actions of individual occupants, and it was necessary to infer the occupant behaviour from these measurements. For example, in the case of wet appliances, the

power demand falls down to 0 Watts at mid-cycle (though it does not switch-off), therefore, each use was manually inspected to ensure the correct switch-on times and switch-off times. The number of wet appliances are 364 which were monitored for 27-30 days. This makes 9,828 individual days to manual inspect and this part of the analysis took a very long time. It could be considered inefficient for modelling as it takes long time.

Larger and more representative studies are required in order to construct models which are influenced by differences across the sample (such as household type, number of occupants, income etc.) which could then be fully assessed through cross-validation and associated techniques.

7.2 APPLIANCE BEHAVIOUR MODELLING AND SIMULATION METHODOLOGIES

The key findings of the thesis are discussed in this section, with reference to the first research question. What is the best approach to model the occupant behaviour of appliance use for demand response studies? Occupant behaviour modelling of household appliances use is still a relatively new field of research and there is more work needed to improve our knowledge of the suitability of the numerous modelling approaches currently available. One of the novel points that were built is that the model procedure consists of threshold parts; i) number of switch-on events in a day, ii) starting time of each event, and iii) duration and power demand of the appliance use. All of those are respectively drawn through stochastic processes. This approach preserved the diversity in occupant behaviour at each metric.

The first major issue is: the difference between intra-household variations (diversity of behaviour within households for different days) and inter-household variations (diversity of behaviour among households) is often ignored in previous modelling studies of household electricity demand. For example, only inter-household variation (variation among different household groups) could be considered for past models that have been developed using time of use datasets based on one-day diaries (Tanimoto

et al., 2008; Richardson et al., 2010; Widén et al., 2012, Wilké et al., 2013). These models averaged the profiles of one-day for different sub-populations to integrate the variation among households. The strength of the HAU model is that it considers multiple stochastic factors within the households: appliance switch-on time probabilities and usage durations developed for individual homes. To do this, individual probability density functions (PDF) for switch-on times and cumulative distribution function (CDFs) for the number of switch-on events and durations explained in Section 3.5.3 were developed. The results of this thesis show that averaging profiles (AvgHs. And AvgApp.) for a population underestimates the variation. This was shown in the box plots in Section 4.3.1 and Section 4.3.2 that averaging the data (AvgHs and AvgApp) similar to Wilké et al (2013) and Richardson et al. (2010) underestimates the diversity. As a result, corresponding uncertainty of building performance simulation predictions may be greatly underestimated. This limits one of the major benefits of stochastic occupant behaviour modelling. Occupant behaviour diversity may be advantageous with regards to instantaneous electricity demand since certain systems must be sized to meet the maximum expected simultaneous load or may underestimate the problem of grid instability (Baetens and Saelens, 2011).

The switch-on times of appliances are predicted based on relative time-of-day use probabilities. This study found that the method which predicted the time when a switch-on event occurs using PDFs gave good results in the case of switch-on times over one day, in agreement with studies in literature which performed similar validation (Page, 2007). The HAU model has proven itself capable of simulating the switch-on times over a day. However, the Approach 1 method of assigning switch-on times based on switch-on PDFs and followed by assigning durations from CDFs is problematic because the means of average daily number of switch-on events are under predicted (shown in Section 4.3.1). This result may arise because of the process of stepping through the time steps in time order and effectively jumping over a number of time steps when a switch-on event occurs and a duration is assigned, reducing the number of times that the PDF is used to test for a switch-on event. This effect is more pronounced in model variant IndHs (where PDFs of switch-on times were developed for each individual household) as the probabilities are more ‘peaky’ and occur at similar times of the day (due to habits of the households), causing the reduction at the

mean values up to 12% (Table 4.6). However, Approach 2 appears to solve this problem and predicts similar numbers of switch-on events compared to the measured data. As discussed in the findings (Chapter 4), the simulation results shown in Table 4.6, Figure 4.7, and Figure 4.13 support the argument that models developed on individual home profiles (IndHs and IndApp) capture the variation (both switch-on probabilities and appliance usage duration) much better than averaged profiles (AvgHs and AvgApp) regardless of whether Approach 1 or Approach 2 is used. This is partly explained by the fact that when a single 'average' CDF is created from the dataset, durations are selected mostly around the median thereby hindering the variation in durations for individual usages; whereas for AvgHs_IndApp the per-appliance CDFs are more diverse resulting in a wider range of values.

In the bottom-up HAU model, the power demand of the appliances for each use are directly assigned from the individual distributions simultaneously with the durations. Power demand readings during the durations were either manually inspected or a code has been developed to derive the values during the duration. Most of the studies in literature that used Time-of-Use datasets use average power demand values for cooking appliances and televisions when converting the activities to power demand profiles assigning power demand for appliance use (Tanimoto et al., 2008; Richardson et al., 2010; Widén et al., 2012). Several studies even use fixed durations and fixed power for each appliance use as well (Paatero and Lund, 2010; Gottwalt et al., 2011). To discuss this issue, Figure 7.1 shows the daily power demand profile of ovens simulated using an average power demand which was calculated from the power demand during appliance use and power demand during appliance use without averaging. When average power is used, the daily power demand profiles of ovens is significantly underestimated up to 50 % during peak times whereas this less than 9 % if the power demand during appliance use without averaging is used. This is due to averaging appliances whose power demand strongly change during their use underestimates the great variety of levels of power during usage. Using power demand without averaging significantly improves the model predictions compared to the average power used.

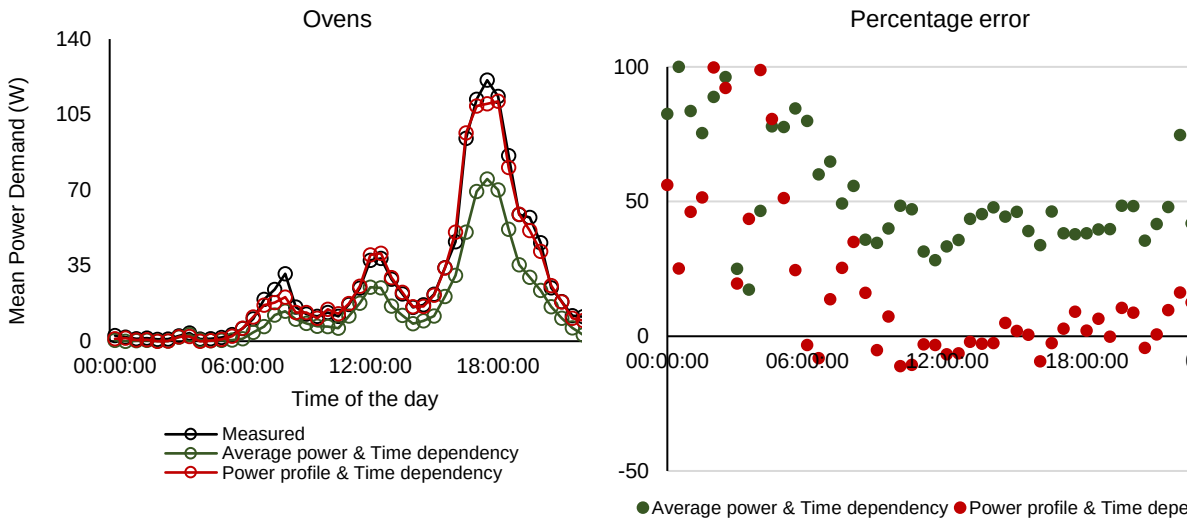


Figure 7.1 Mean half-hourly power demand profiles of oven modelled with average power values and power demand profiles and percentage error plot of the power demand profile.

For televisions, this averaging effect was not as significant for the cooking appliances (Figure 7.1). This is due to the fact that power demand of televisions are usually constant (although the power demand fluctuates a little as shown in Figure 5.8) during the usage however for cooking appliances power demand varies quite randomly during the usage (occupants change the settings to low or higher heat).

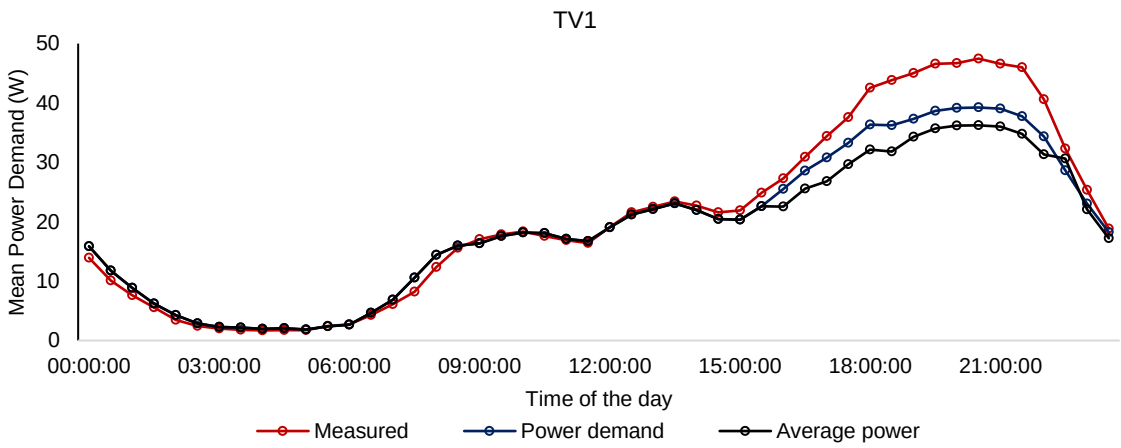


Figure 7.2 Mean half-hourly power demand profiles of TV1 modelled with average power values and power demand profiles

The findings for ovens and televisions show that approach in previous significantly underestimates the daily power demand profile as it averages the different levels of power demand during the appliance use (households changing the power of the

cooking hob, or changing the temperature of the oven). It shows that even though other behaviour metrics such as the number of switch-on events, switch-on times and durations were predicted correctly, the daily power demand profiles will not match if these metrics are converted to power demand profiles by using average and fixed power demand for appliance use.

Another key finding of this study is that for several appliances such as televisions and cooking appliances, the duration of the appliance use significantly depends on the hour slot when the appliance use starts (Section 4.2.3). For cold and wet appliances, this was not the case. Wilké et al. (2013) found this relation in their dataset too. Dividing the switch-on events for different hour slot introduced data scarcity issues in particular during the night as there is an insignificant (or even zero) quantity of times the corresponding activity in those time intervals. Therefore, when creating CDFs of duration of use for different time slot, for the time slots that are not significantly different to each other (Post-Hoc), CDFs were not developed for each hourly slots but a group of time slots. To give an example, CDFs of duration of use of cooking appliances were developed for time slots (00:00 to 06:00, 06:00 to 08:00 …..….. 19:00, 20:00, 21:00, 22:00 to 00:00). Simulation results presented in Section 5.3.2 shows that if the time-dependency was not considered when assigning the durations and power demand of the appliances, the peak power was underestimated. The HAU model algorithms make sure that the process of stepping through the time steps goes until the condition (number of switch-on event for that day chosen from the CDF) is met. However, this result may arise because of the process of stepping through the time steps in time order and effectively jumping over a number of time steps when a switch-on event occurs and a duration is assigned, when longer durations at the earlier times of the day are assigned it reduces the number of times that the PDF is used to test for a switch-on event during the peak. The results show that the effect of this problem is reduced when the duration of use assigned depending on the time slot the appliance is switched-on therefore matching the power with the measured data at peak time.

For cold appliances, off-sequence durations (when the compressor is not on) has not been discussed in this study. Although Approach 2 predicts the number of times when the compressor switches on, it has no constraint for the off-durations, therefore the sequences might be quite uneven. A future approach might be to determine an on-sequence profile from CDFs of on-durations and, once the on-sequence ends, the

duration of the off-sequence could be deduced from an equivalent off-sequence duration profile.

Overall, the HAU model correctly predicted the three appliance behaviour metrics which are number of switch-on events in a day, starting time of each appliance use, and duration of appliance use (Table 4.6, Table 4.7, Figure 4.9 to Figure 4.12). However, results presented in Section 5.3.1 show that discrepancies were seen between the appliance power demand profiles.

It is worth mentioning that simulations for cold appliances took longer time than the rest of the appliances. The reason for that the number of switch-on events per day changes between 0 to 148 whereas for other appliances it changes between 0 to 13 maximum. The process of stepping through the time steps goes until the condition met; therefore, it took longer time to complete.

7.3 METHODOLOGIES FOR THE ASSESSMENT OF HOUSEHOLD APPLIANCE USAGE MODELS

One objective of this study was to validate the model against the actual data and external data. Prior to this research, there was no peer reviewed published literature to compare the average number of switch-on events per day (mean value and the variation) and duration per appliance use (mean value and the variation). Comparison of switch-on times and power demand profiles (though not on appliance level) exist (Tanimoto et al., 2008; Richardson et al., 2010; Widén et al., 2012, Wilké et al., 2013). This study made sure that the validation was done on metric level and appliance level to identify the discrepancies and comment on them.

Firstly, the ability of the model variants to predict the demand patterns in the monitored dataset was compared in order to test the mathematical formulas behind the model. In this case, therefore, cross validation (where the monitored data is divided into training and test sets) was not performed in order to prevent the bias when comparing the approaches. The simulation results were compared with the entire dataset. Here the HAU model was run for 100 times to produce distributions of simulation results for the parameters of interest. This is necessary for a stochastic model as a single model run could easily return extreme values (from the tails of the expected distribution of

values). It was mentioned in Section 7.1 that there was little consistency across homes with respect to which appliances recorded. Therefore, splitting this dataset up into separate "training" and "testing" datasets is questionable if we want to test generalisation across homes.

Secondly, the HAU model was compared with two external datasets. It is quite rare to see the electricity demand models compared with external data due to lack of datasets. The yearly electricity consumption of the individual appliances and daily electricity power demand profiles were compared to two different studies. The “Energy Consumption in UK” was used to compare the electricity consumption of individual appliances and the dataset of Elexon was used to compare the daily electricity power demand profiles with the HAU model simulation results. The ECUK Tables were formed based on different data sources using the Cambridge House Model and based on data provided by Market Transformation Programme (MTP). However, these results did not match perfectly as expected due to different data resources. To do rigorous verification, we need more of high-quality disaggregated electricity data.

7.4 DEMAND RESPONSE MODELLING

Part of the aim of this programme of research was to assess the power demand flexibility and to quantify the demand response potential of the UK homes. Demand response cases are applied stochastically using the HAU model. The key findings of Chapter 6 with reference to the second research question (Q2: To what extent can the household electricity demand be shaped with demand response (shifting the time of the demand)?) are discussed below.

The extent of flexibility that can be offered by the home appliances was assessed. To assess it, demand response was stochastically modelled by shifting the appliances under different probabilities (Table 6.11) that were determined randomly. The simulation results of demand response models presented in Section 6.4 show that ovens have the highest absolute decrease of the electricity consumption from the peak period (0.09 kWh) per household and have the highest absolute decrease of average

power demand from the average peak demand (decrease of 41.7 Watts from the highest peak power demand) per household. Ovens are followed by tumble dryers and dishwashers which the shifting had caused an absolute decrease of the electricity consumption from the peak period 0.05 and 0.04 kWh per household, respectively. These results highlighted that ovens can offer a significant flexibility more than other appliances shifted if they are switched-on at a later time (almost twice as much as tumble dryers and dishwashers). However, several studies discussed routines and practises as a reason not to engage in demand response (Balta-Ozkan et al., 2013; Darby & Pisica, 2013). Fell (2016) showed that concerns about shifting cooking appliances came out most strongly. Moreover, occupants that are working might not be able to use electricity for cooking a different time because they would not physically be there to do so. Therefore, it is important to note that the results are the assessment of technical possibilities (what if 20% or 40% are willing to shift to later time) to quantify the potential of demand response that utilities can expect, other constraints such as presence of a person, or people's preference were not considered.

The extent of flexibility that can be offered by home appliances can also be addressed with a different metric. This metric can be the decrease of total electricity demand from the peak demand per number of shifted appliances (Wh/appliance). The simulation results in Section 6.3.2 show that although the absolute decrease of the electricity consumption from the peak period (0.09 kWh) per household by shifting the ovens, the decrease of total electricity demand from the peak demand per shifted appliances was 511 Wh for ovens which was lower than dishwashers and tumble dryers which were 1136.5 Wh and 1276.4 Wh. Ovens have the highest contribution to the peak time due to their high saturation level, high number of switch-on events during peak time and average power per usage. However, this metric shows that the amount of flexible demand offered by per appliance shift is higher for dishwashers and tumble dryers than those to ovens. Overall, the simulation results in Section 6.4 have shown that shifting appliances to a later time is likely to produce more levelled demand patterns by decreasing the evening peak and increasing power demand late in the evening. Peaks in the network demand pattern can be reduced by 87.9 Watts from the total peak with the six appliances chosen which corresponds to 13% (total peak power per household is 677 Watt calculated from the HES dataset).

Stochastic demand response was modelled by shifting the appliances (rescheduling) individually. In demand response simulations, only six different appliances were shifted, because their saturation levels and electricity consumption are high (see the criteria in Table 3.11) and these appliances are considered as shiftable appliances in literature (Table 2.7). However, the HAU model enables to work with other appliances as every appliance was modelled individually with a bottom-up approach. Household appliance runtimes and appliance-specific constraints should be considered. For example, cold appliances cannot be shifted more than one hour (Paatero and Lund, 2006).

Demand response modelling structure was similar to the study of Gottwalt et al. (2011). Similar to Gottwalt et al. (2011), probability for the shift of an appliance to a later time had to be assumed as there are no reliable empirical data available. In this simulation, distinct scenarios were used for the probability of shifting the appliance to a random time after 9pm and before midnight. Another possible way of modelling the demand response is to simulate changes in the profiles when households face time-based electricity prices. In this case, the algorithm randomly selects one of the cheapest slots to shift the appliances to. In this way, the gaps can be filled resulting in a more levelled demand pattern.

A number of assumptions were made in modelling the demand response. First of all, demand response was applied only to the households who had a switch-on event of an appliance for that particular day. This is done to ensure not to create extra events for the day. Secondly, if there is a switch-on event of the appliance in the off-peak time, the appliance on the peak time is not shifted to the off-peak time. For modelling purposes, this assumption had to be made in order to not overlap with the same appliance use in the late evening. However, in reality the occupants might still want to shift their appliances arranging the appliances of peak time to a late evening and cancelling the same activity at late night. More research is needed to understand if this assumption is valid.

8 CONCLUSION

This thesis sets out to investigate new approaches to household appliance usage and occupant behaviour modelling to generate realistic electricity demand profiles for domestic appliance use that are based on measured data. This included a focus on appliance and occupant behaviour modelling and converting these into power demand profiles. The last stage of research focused on the application of demand response cases using the developed household appliance usage model. The conclusion chapter briefly summarises the key findings in relation to the research questions, states original contributions to knowledge made by this research and outlines their significance for research, industry and policy.

8.1 SUMMARY OF KEY FINDINGS

Analysis of the HES dataset found out five findings:

- There is a significant variation between households in the average number of appliance switch-on events (Table 4.1) and also in number of switch-on events across days (Figure 4.2).
- There is a further variation in the switch-on times of appliances across different days and households for all 16 appliance types (Figure 4.3). Cooking appliances are switched-on around morning, noon and evening times (presumably meal times). Peak time occurs in the evening for dishwashers after the evening meal, whereas the peak time for washing machines is observed in the morning. Cold appliances switch-on repeatedly throughout the day.
- Duration of the appliance use is also highly variable and average household appliance durations vary significantly (Table 4.4). Individual appliance use duration lengths also vary (Figure 4.6).
- For cooking appliances and televisions, there is a significant effect of hour slots when the appliance is started on the duration of use of appliances (Figure 4.5).

- There is a significant variation of average measured electricity consumption per day households (Table 5.1) and in power demand of appliances across different time of the day for all 16 appliance types (Figure 5.3).
- Analysis shows that programme of choice as a metric is as important as the other metrics for wet appliances, cooking appliances and electric showers. Though same duration can be used for another usage, the power demand profile/level is different to each other (Figure 5.5, Figure 5.7 and Figure 5.9).

Household appliance usage model was constructed and appliance behaviour metrics and daily power demand profiles were simulated using different modelling approaches. Comparing the simulation results with those measured revealed that:

- The modelling approach (Approach 2) that proposes to assign first the daily number of switch-on events, and then determines the time of the switch-on events by 'stepping through' the PDF and durations from CDFs, predicts the average daily number of switch-on events correctly (Figure 4.6 and Table 4.6). Approach 1 (similar to previous studies) does not first assign the daily number of events and simply determines the number of switch-on events and switch-on times by 'stepping through' the PDF and durations from CDFs. Approach 1 was shown to significantly underestimate the average daily number of switch-on events.
- The model variants that use individual household switch-on PDFs and individual appliance duration CDFs simulated variation in average daily number of switch-on times and durations better than those model variants developed based on averaged households and averaged appliances (Figure 4.9 and Figure 4.13).
- Power demand profiles per day of appliances were predicted well for 16 appliance types. However, peak values were underestimated up to 12% for most of the appliances.
- Averaging the power demand profiles of appliances whose power fluctuates during use (cooking appliances) is disadvantageous when simulating appliance power demand profiles (Figure 5.20).
- Durations of appliances which have time-dependency (Figure 4.16), should be modelled depending on the time-slot the activity starts so as not to underestimate the peak power (Figure 5.22).

The amount of flexible demand and potential for demand response were calculated using the HAU model. For this, the demand response cases applied using the HAU model. The simulation results of demand response modelling suggested that:

- Simulation results show that the amount of flexible demand available during peak load is a combination of appliance ownership and probability of switch-on events during the peak load.
- Shifting the appliances has different effects on the electricity consumption. For example, ovens have the highest absolute decrease of the electricity consumption from the peak period (2064.1 MWh) for the national scale and have the highest absolute decrease of average power demand from the average peak demand (decrease of 56.7.5 Watts from the highest peak power demand) per household (Table 6.12).
- Tumble dryers have the highest decrease of total electricity demand from the peak demand per shifted appliances (1276.4 Wh), it is followed by dishwashers and washing machines which are 1136.5 kWh and 830.2.2 Wh, respectively (Table 6.12).

8.2 IMPLICATIONS FOR RESEARCH, PRACTICE AND POLICY

This study has contributed to an improved understanding of the occupant behaviour of household appliance use in the UK homes. Monitored power recordings of electrical appliances have been analysed in details and occupant behaviour metrics were calculated for 1,076 appliances in 225 households from the UK Government's Household Electricity Survey carried out in 2010-2011. The analysis showed that occupant behaviour varies substantially across households, across appliance types and over time. Many studies have shown that duration of appliance use differ in between different in a day or next day, however the analysis of power demands of this thesis that choice of programme is also an important factor modelling the household appliance power demand as power demand per each usage is different. This research shows that although the first three appliance behaviour metrics, number of switch-on events per day, switch-on times, and duration of appliance usage, are predicted

correctly, discrepancies occur if the power demand for usage is modelled with average and fixed power demand profiles.

The study set out some guidelines on identifying appliance behaviour metrics from the monitored 2-minutely power demand measurements in Section 3.5.1. This could help researchers when analysing their own dataset and be aware of the error that can be found in the power measurements of the appliances.

Modelling the use of appliances is a challenging task, given the diversity of appliances available and the variability in occupant behaviour from one household to another household. The main conclusion for the research community who is interested in definition and simulation of occupant behaviour in buildings is that averaging the data for developing the metrics is shown to suppress the diversity of the occupant behaviour within the individual households and this variation is often ignored by modellers in literature as they use Time of Use datasets based on diaries recorded in a single day to develop their models. However, the results here show that variation within the individual households is an important factor and the choice of modelling approach can play a significant role in predicting the occupant behaviour of appliance usage.

While the importance of modelling demand response is well recognised in research, there is a limited research aimed to explore the flexibility that can be offered by individual electric appliances. It is hoped that policy makers with an interest in time shifting of appliances to match supply and demand will be able to draw on these key findings to structure their demand response cases. The research has a range of implications for targeting demand response services. Particular aspects of the system have been focused on which can be seen as key to enabling flexibility. First implication is the total effect of shifting appliances per household that could be interesting for utility companies. The simulation results of the demand response show that ovens have the highest absolute decrease of the electricity consumption from the peak period (decrease of 0.09 kWh) and the highest absolute decrease of average power demand from the average peak demand (56.7 Watts) per household. Ovens were followed by tumble dryers and dishwashers which had 0.06 and 0.05 of absolute decrease of the electricity consumption from the peak period (kWh) per household which was almost half of the effect of ovens. Comparison between different demand case (Figure 6.3 and Figure 6.4) shows that convincing 40% of the households to shift their

dishwashers or tumble dryers can lead to same decrease for households with ovens where 20% of the households agrees to shift their usage of ovens. These comparisons can be useful for policy makers

Second implication is the individual effect of shifting appliances on the household electricity demand profile which could be interesting for the households. Decrease of total electricity demand from the peak demand per shifted appliances was the highest for dishwashers and tumble dryers which are 1136.5 Wh and 1276.4 Wh (Table 6.12). This could be interesting for the households who want to prioritise some appliances over others considering their routines and practises.

There is a common perception that electric utilities will benefit from demand side management, for example, in the form of a reduction in the generation costs, less balancing power transportations and thus less transmission grid investments, and increased operation efficiency. However, the findings suggest the likely emergence of alternative demand peaks by shifting appliances to a later time (shown in Figure 6.3 and Figure 6.4) which could significantly underestimate the benefits of the demand response.

8.3 OVERALL CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

In conclusion, this work provides a new bottom-up model to predict household appliance usage and the appliance power demand profiles of some household electric appliances based on the field measurement data that UK government did in 2011 as a huge campaign. The modelling approach that was proposed was good at capturing the appliance behaviour metrics and overall household appliance power demand profiles. In future work, the current study can be extended to include more appliances in the HAU model and analysis of the potential for interaction between the use of difference appliance types could help to improve the household appliance usage model.

More data collection is encouraged especially for the appliances which are of small size such as hobs. This will help to run ANOVA tests to test the difference between

different household and day groups. Additionally, the length of the monitoring period can be extended to include better analysis of seasonality effect on the uccupant behaviour. Both 2011 HES and 2011 EFUS was conducted in 2011. Whilst occupancy patterns and appliance ownership rate may not have changed dramatically for most of the appliances; for modelling the total electricity demand profiles the evolution in the use of electronic devices calls for a careful consideration of “old” time use data in relation to “new” timing of residential electricity demand. Therefore, more nation-wide surveys should be done. More households would also help to decreasing the issues of data scarcity in order to run cross-validation.

9 REFERENCES

Abushakra B., Sreshthaputra A., Haberl J., Claridge, D. (2001). Compilation of diversity factors and schedules for energy and cooling load calculations (Technical report). Energy Systems Laboratory, Texas A and M University.

Aigner,D., Sorooshian,C., Kerwin, P. (1984). Conditional Demand Analysis for Estimating Residential End-Use Load Profiles. *The Energy Journal* Vol. 5(4), pp. 81–97.

Armstrong, M., Swinton, M., Ribberink, H., Beausoleil-Morrison, I., Millette, J. (2009). Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing. *Journal of Building Performance Simulation*. Vol. 2(1), pp. 15-30.

Aydinalp, M., Ugursal, V., Fung, A.S. (2003). Modelling of residential energy consumption at the national level. *International Journal of Energy Research* Vol. 27(4), pp. 441–453.

Boardman, B., Darby, S., Killip, G., Hinnells, M., Jardine, C., Palmer, J., Sinden, G. (2005), 40 % House. Available from: http://goo.gl/5RYzYL. Accessed on the 4th April 2014.

Bhartiya, N., Narayanamoorthi, R., Senthilmurgan, S., Juliet, A.V. (2012). Voltage Control in Grid Connected Wind Farm Generator for Better Connectivity. *International Journal of Management & Business Studies.* Vol. 9(4), pp. 81-84.

Baltagi, B. (2002). Comparison of forecast performance for homogeneous, heterogeneous and shrinkage estimators: Some empirical evidence from US electricity and natural-gas consumption. *Economics Letters*. Vol. 76(3), pp. 375–382.

Baghina, N., Lampropoulos, I..Asare-Bediako, B., Kling, W.L., Ribeiro, P.F (2012). Predictive control of a domestic freezer for real-time demand response applications. In: Proceedings of 3rd IEEE PES International Conference and Exhibition Innovative Smart Grid Technologies (ISGT Europe), Berlin, Germany, pp.1-8.

Bedir, M., Hasselaar, E., & Itard, L. (2013). Determinants of electricity consumption in Dutch dwellings. *Energy and Buildings*. Vol. 58, pp. 194–207.

Belhomme, R., Sebastian, M., Diop, A., Entem, M., Bouffard, F., Valtorta, G., De Simone, A., Cerero, R., Yuen, C., Karkkainen, S., Fritz, W. (2009), ADDRESS Technical and Commercial Conceptual Architectures. Available from: http://goo.gl/xlqSfw. Accessed on the 19th May 2014

Black, M., Strbac, G., (2007). Value of Bulk Energy Storage for Managing Wind Power Fluctuations. *IEEE Transactions on Energy Conversion*. Vol. 22(1), pp. 197-205.

Baetens, R., De Coninck, R., Helsen, L., Saelens, D. (2010). The impact of load profile on the grid-interaction of building integrated photovoltaic (BIPV) systems in low-energy dwellings. *Journal of Green Building.* Vol. 5(4), pp 137-147.

Bartiaux, F., & Gram-Hanssen, K. (2005). Socio-political factors influencing household electricity consumption: A comparison between Denmark and Belgium. In What works & who delivers?. *In Proceedings of the ECEEE 2005 Summer Study, European Council for an Energy Efficient Economy,* pp. 1313–1325.

de Blécourt M. (2012). Smart scheduling of smart household appliances using an Agent-Based Modelling Approach. MSc. Delft University of Technology

Belhomme, R., (2009). ADDRESS Technical and Commercial Conceptual Architectures. In *Deliverable 1.1*, 85.

Bulkeley, H., Bell, S., Lyon, S., Powells, G., Judson, E. and Lynch, D. (2014) Customer-Led Network Revolution Durham University Social Science Research: April 2014 Report, Durham, UK, Durham University. Available from: goo.gl/BmmeST. Accessed on the 7th August 2016.

Capgemini (2008), Demand Response: a decisive breakthrough for Europe. Available from: http://goo.gl/nlKy7o. Accessed on the 1st March 2014.

Capasso, A., Grattier, W., Lamedica, R., Prudenzi, A. (1994). A bottom-up approach to residential load modelling. *IEEE Transactions on Power Systems*. Vol. 9(2), pp. 957–964.

Carlson, D. R., Scott Matthews, H., & Bergés, M. (2013). One size does not fit all: Averaged data on household electricity is inadequate for residential energy policy and decisions. *Energy and Buildings*. Vol. 64, pp. 132–144.

Carmichael, R., Schofield, J., Woolf, M., Bilton, M., Ozaki, R. and Strbac, G. (2014) Residential consumer attitudes to time-varying pricing, Report A2 for the 'Low Carbon London' LCNF project. Available from: goo.gl/Dzpgf1. Accessed on the 4th November 2016.

Committee on Climate Change (2008). Building a low-carbon economy – the UK's contribution to tackling climate change. Available from: http://goo.gl/S3WJ0z. Accessed on 5th January 2014.

Department for Communities and Local Government (2014). English Housing Survey: TECHNICAL REPORT 2013-14. Available from: http://www.data-archive.ac.uk/

DECC (2010a). 2050 Pathways Analysis. Department of Energy and Climate Change. Available from: https://www.gov.uk/2050-pathways-analysis. Accessed on 29th January 2016.

DECC (2010b). How Trends in Appliances Affect Domestic CO2 Emissions: A review of Home and Garden Appliances. Department of Energy and Climate Change. Available from: http://goo.gl/SeZlHl. 4th April 2014.

DECC (2011). Microgeneration Strategy. Department of Energy and Climate Change. Available from: http://goo.gl/NfAhWq. Accessed on the 2nd July 2014.

DECC (2012), Demand Side Response in the domestic sector- a literature review of major trials. Department of Energy and Climate Change. Available from: http://goo.gl/MX7JnO. Accessed on the 15th May 2012.

DECC (2013a). Early Findings: Demand side management, Department of Energy and Climate Change. Available from: http://goo.gl/aw9Iuj. Accessed on the 4th April 2014.

DECC (2013b). Energy Consumption in the UK: Chapter 1, Overall Consumption. Department of Energy and Climate Change. Available from: http://goo.gl/9ddULW. Accessed on 10th February 2014.

DECC (2013c). Digest of UK Energy Statistics (DUKES). Department of Energy and Climate Change. Available from: http://goo.gl/PDstxq. Accessed on the 25th March 2014.

DECC (2013d). Domestic energy consumption in the UK between 1970 and 2012. Department of Energy and Climate Change. Available from: http://goo.gl/jTLbsV Accessed on the 10th February 2014.

DECC (2013e). Energy Consumption in the UK (ECUK); domestic data tables. Department of Energy and Climate Change. Available from: http://goo.gl/jTLbsV Accessed on the 25th March 2014.

DECC (2013f). Energy Consumption in the United Kingdom (ECUK), User Guide. Department of Energy and Climate Change. Available from: http://goo.gl/jTLbsV. Accessed on the 25th March 2014.

DECC (2013g). Household Electricity Survey. Department of Energy and Climate Change. Available from: http://goo.gl/n0MH0A. Accessed on the 5th October 2014.

DECC (2014a). United Kingdom housing energy fact file: 2013. Department of Energy and Climate Change. Available from: http://goo.gl/8Z3fr6. Accessed on the 25th March 2014.

DECC (2014b). English Housing Survey. Department of Energy and Climate Change. Available from: http://goo.gl/r26r6H. Accessed on the 25th March 2014.

DECC (2014c). Helping households to cut their energy bills. Department of Energy and Climate Change. Available from: http://goo.gl/3jUoSr. Accessed on the 10th February 2014.

DECC (2014d). Energy efficient products helping us cut energy use. Department of Energy and Climate Change. Available from: http://goo.gl/UwWfAe. Accessed on the 30th November 2014.

DECC, BRE (2014). Energy Follow Up Survey, 2011. 2nd Edition. UK Data Service. SN: 7471, Department of Energy and Climate Change, Building Research Establishment. Available from: http://dx.doi.org/10.5255/UKDA-SN-7471-2. Accessed on the 4th October 2015.

DECC (2015). Cambridge Housing Model and user guide. Department of Energy and Climate Change. Available from: goo.gl/g05531. Accessed on the 17th October 2016.

De Coninck, R., Helsen, L. Bottom-Up Quantification of the Flexibility Potential of Buildings. In Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28.

DEFRA (2011). Market Transformation Programme. The Department for Environment, Food and Rural Affairs. Available from: http://efficient-products.ghkint.eu/. Accessed on the 5th September 2016.

EFFLOCOM Partners, (2004). Energy efficiency and load curve impacts of commercial development in competitive markets, Results from the EFFLOCOM Pilots. Available from: http://goo.gl/gRSdcm. Accessed on the 7th March 2014.

Element Energy (2012) *Demand side response in the non-domestic sector*, Final report for Ofgem, London, UK, [online] Available from: goo.gl/QAe2uj (Accessed 4 December 2015).

Ehrhardt-Martinez, K., Donnelly, K., Laitner, J.A., York, D., Talbot, J., Friedrich, K., (2010). Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Economy-wide Electricity Savings. (No. E105). American Council for an Energy-Efficient Economy, Washington, D.C.

Elexon (2016). Load Profiles and their use in electricity Settlement Available from: https://www.elexon.co.uk/reference/technical-operations/profiling/. Accessed on the 7th October 2016.

ENA and Energy UK (2012). Smart Demand Response: A Discussion Paper. Energy Network Association. Available from: goo.gl/iMQtY8. Accessed on the 13th February 2014.

Energy Follow-Up Survey, (2011). Domestic appliances, cooking & cooling equipment. Building Research Establishment. Available from: http://goo.gl/nUYNeS. Accessed on the 4th April 2014.

Energy Follow-Up Survey, (2011). Report 8: Lighting. Building Research Establishment. Available from: http://goo.gl/trZ6fq. Accessed on the 16th April 2014.

Energy Retail Association (2008), Report stage of the energy bill by Lord Hunt of Kings Heath, Press Release, Available from: http://www.energyretail.org.uk/media/press/2008/ERASmartMetermandateOct08.html.

EPRI (2009). Residential electricity use feedback: A research synthesis and economic framework. Technical report, Electrical Power Research Institute. Available from: http://goo.gl/2cvHel. Accessed on the 5th July 2014.

Esser, A., Franke, M., Kamper, A., 2006. SESAM Arbeitspaket 3.7: Simulation und Einplanung dezentraler Energieerzeugungsanlage. Project Report, Karlsruhe.

European Commission (2006). Communication on a first assessment of National Energy Efficiency Action Plans, COM 545. Brussels: European Commission.

European Commission (2013). Incorporating demand side flexibility, in particular demand response, in electricity markets. Available from: http://goo.gl/CQcPq4. Accessed on the 2nd April 2014.

Faruqui, A, George, S. (2005). Quantifying customer response to dynamic pricing. *Electrical Journal*. Vol. 18(4), pp. 53-63.

Faruqui, A., Sergici, S., Shultz, E., (2013). Consistency of Results in Dynamic Pricing Experiments – Toward a Meta-Analysis. Proceedings of DistribuTECH Conference, San Diego, CA, United States.

Fawcett, T., Lane, K., Boardman, B. (2000), Lower Carbon Futures for European Households. Available from: http://goo.gl/dtOHdq. Accessed on the 4th April 2014.

Fell, M.J., Nicolson, M., Huebner, G.M., Shipworth, D. (2015). Is it time? Consumers and time of use tariffs. Trialling the effect of tariff design and marketing on consumer demand for demand-side response tariffs. Available from: goo.gl/W6eMDF. Accessed on the 4th April 2014.

Fell, M.J. (2016). Taking Charge: Perceived control and acceptability of domestic demand-side response. PhD, University College London.

Freris, L., Infield, D. (2008). *Renewable Energy in Power Systems*. 1 edition, page 23. Chichester, United Kingdom: John Wiley & Sons.

Frontier Economics and Sustainability First (2012). Demand Side Response in the domestic sector- a literature review of major trials. Available from: http://goo.gl/tisNbl. Accessed on the 8th April 2014.

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy? *Energy Efficiency.* Vol. 1(1), pp. 79-104.

Fujimoto, T., Yamaguchi, Y., Shimoda, Y. (2011). Household Electricity Simulation: Demand, the Electricity Generation and Demand-Supply Control Methods. . In: Proceedings of the 12th Conference of International Building Performance Simulation Association, Sydney, Australia, pp. 996–1003.

Gandjean, A., Adnot. J., Binet, G. (2012). A review and an analysis of the residential electric load curve models. *Renewable and Sustainable Energy Reviews.* Vol. 16(9), pp. 6539-6565.

Genjo, K., Tanabe, S., Matsumoto, S., Hasegawa, K., & Yoshino, H. (2005). Relationship between possession of electric appliances and electricity for lighting and others in Japanese households. *Energy and Buildings*, Vol. 37(3), pp. 259-272.

Gottwalt, S., Ketter W., Block, C., Collins J., Weinhardt, C. (2011). Demand side management—A simulation of household behavior under variable prices. *Energy Policy*. Vol. 39, pp. 8163–8174.

Grandjean, A., Adnot, J., Binet, G. 2012. A review and an analysis of the residential electric load curve models. Renewable and Sustainable Energy Reviews. Vol. 16 (9), pp. 6539-6565.

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

Guerra Santin, O., Itard, L., Visscher, H. (2009). The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings.* Vol. 41(11), pp. 1223–1232.

Halvorsen, B., & Larsen, B. M. (2001). Norwegian residential electricity demand – a microeconomic assessment of the growth from 1976 to 1993. *Energy Policy*. Vol. 29(3), pp. 227–236.

He, J., Young, A.N., Pathan, A. Oreszczyn, T. (2005). Air conditionin Energy Use in Houses in Southern England. In Proceeding of Dynamic Analysis, Simulation and Testing Applied to the Energy and Environmental Performance of Buildings Conference, Athens, Greece.

Hidalgo González, I., Ruiz Castello, P., Sgobbi, A., Nijs, W., Quoilin, S., Zucker, A., Thiel, C. (2015). Addressing flexibility in energy system models. Joint Research Centre Scientific and Policy Report. Available from: goo.gl/NM33rR. Accessed on the 15th September2016.

HM Government (2011). The Carbon Plan: Delivering our low carbon future. Available from: http://goo.gl/69yg3c. Accessed on the 5th December 2013.

Hoes P., Hensen J.L.M., M.G.L.C. Loomans M.G.L.C., de Vries B., Bourgeois D. (2009). User behavior in whole building simulation. *Energy and Building*. Vol. 41(3). Pp. 295–302.

Household Electricity Survey, (2011). Electrical appliances at home: tuning in to energy saving. Department of Energy and Climate Change. Available from: http://goo.gl/GV3jga. Accessed on the 15th April 2014.

IEA (2003). The Power to Choose, Demand Response in Liberalised Electricity Markets. International Energy Agency. Organisation for Economic Co-operation and Development. Paris, France. Available from: http://www.oecd-ilibrary.org/energy/the-power-to-choose_9789264105041-en. Accessed on the 1st March 2014.

IEA (2011), Implementing Agreement on Demand-side Management Technologies and Programmes (2010 Annual Report): International Energy Agency - DSM. Available from: http://www.ieadsm.org/Publications.aspx?ID=24. Accessed on the 4th April 2014.

Isaksson, C., Karlsson, F. 2006. "Indoor climate in low-energy houses - an interdisciplinary Investigation." Building and Environment 41 (12): 1678-1690.

Mourik, R.M., van Summeren, L.F.M., Breukers, S., Rotmann, S. (2015). Did you behave as we designed you to? Technical report: Task 24 Phase I Subtask 3 Closing the Loop Behaviour Change in DSM: From Theory to Practice. Available from: http://www.ieadsm.org/task/task-24-phase-1/. Accessed on the 12th September 2016.

Kamilaris, A., Pitsilledes, A. (2011). Exploiting Demand Response in Web-based Energy-aware Smart Homes.

Kondoh, J., Lu, N., Hammerstrom, D.J. (2011). An Evaluation of the Water Heater Load Potential for Providing Regulation Service. *IEEE Transactions on Power Systems*. Vol 26(3), pp. 1309-1316.

Leahy, E., Lyons, S., (2010). Energy use and appliance ownership in Ireland. *Energy Policy*. Vol. 38(8), pp. 4265-4279.

Leahy, E., Lyons, S., Walsha, S. (2012), Electrical Appliance Ownership and Usage in Ireland. Available from: http://goo.gl/4MHI2G. Accessed on the 4th April 2014.

Lorubio, G. (2011) Flexibile generation: Backing up renewables. Technical report, EurElectric. Available from: http://goo.gl/RaRVZW. Accessed on the 5th July 2014.

Mansouri,I., Newborough, M., Probert, D. (1996). Energy consumption in UK households: Impact of domestic electrical appliances. *Applied Energy.* Vol. 3(211), pp. 211-285.

Muratori, M., Roberts, M.C., Sioshansi, R., Marano, V., Rizzoni, G. (2013). A Highly Resolved Modeling Technique to Simulate Residential Power Demand. *Applied Energy Volume.* Vol 107, pp. 465–473.

McKenna E. (2013). *Demand response of domestic consumers to dynamic electricity pricing in low-carbon power systems.* PhD, Loughborough University.

Moreno, F., Garcia, M., Marin, G., Lazaro, G., Bel, A. (2004). An integrated tool for assessing the demand profile flexibility. *IEEE Transactions on Power Systems.* Vol. 19(1), pp. 668–75

National Action Plan for Energy Efficiency (2010). Coordination of Energy Efficiency and Demand Response. Prepared by Charles Goldman (Lawrence Berkeley National Laboratory), Michael Reid (E Source), Roger Levy, and Alison Silverstein. Accessed from: http://goo.gl/6sZIzb. Accessed on the 3rd May 2014.

National Grid (2009). Policy brief: Operating the system beyond 2020. Available from: http://www.nationalgrid.com/NR/rdonlyres/45D855F7-32B6-41E5-9BD5-1B9A65DB9197/35114/FactSheet2020SO1.pdf. Accessed on 10th December 2012.

Ofgem (2010). Demand Side Response: A Discussion Paper. Available from: http://goo.gl/cWx3EL. Accessed on 10th February 2014.

Oseni, M. O., Pollitt, M. G., Reiner, D. M., Richter, L.-L., Chyong, K. and Baddeley, M. (2013) *2013 EPRG Public Opinion Survey: Smart Energy – Attitudes and Behaviours*. Available from: goo.gl/kcb4hG. Accessed on the 5th July 2016.

Owen, G., Ward, J. (2010). Smart Tariffs and Household Demand Response for Great Britain. Available from: http://www.sustainabilityfirst.org.uk/publications.htm. Accessed on the 5th July 2014.

Owen, G., Ward, J. (2007). Smart meters in Great Britain: the next steps? Paper 6: Case studies. Available from: http://goo.gl/yTSeyF. Accessed on the 4th April 2014.

Page, Jessen 2007. “Simulating occupant presence and behaviour in buildings” PhD, École Polytechnique de Fédérale Lausanne.

Paatero, J.V., Lund, P.D. (2006). A model for generating household electricity load profiles. International Journal of Energy Research. Vol. 30 (5), pp. 273–290

Parti, M., Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. *The Bell Journal of Economics*. Vol. 11 (1), pp. 309–321.

Platchkov, L., Pollitt, M. G., Reiner, D. and Shaorshadze, I. (2011) *2010 EPRG Public Opinion Survey: Policy Preferences and Energy Saving Measures*, EPRG Working Paper, Cambridge, UK, University of Cambridge, Energy Policy Research Group. Available from: goo.gl/9h2hN. Accessed on the 4th April 2016.

Pourmousavi, S.A., Patrick, S.N., Nehrir, M.H. (2014), Real-Time Demand Response through Aggregate Electric Water Heaters for Load Shifting and Balancing Wind Generation. IEEE Transactions on Smart Grid. Vol. 5(2), pp. 769-778.

Raw, G., Ross, D. (2011). *Energy Demand Research Project: Final Analysis*, Report to Ofgem, AECOM. Available from: goo.gl/wkm6Gv. Accessed on the 1st October 2016.

Richardson, I., Thomson, M., Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings*. Vol. 40, pp. 1560–1566.

Richardson, I., Thomson, M., Infield, D., Clifford, C. (2010). Domestic electricity use: a high-resolution energy demand model. *Energy and Buildings.* Vol. 42(10), pp. 1878–87.

Richardson, I. (2010). *Integrated High-resolution Modelling of Domestic Electricity Demand and Low Voltage Electricity Distribution Networks*. PhD. Loughborough University.

Roofegari, N.R., Moghaddas-Tafreshi, S.M. (2012). A novel method for demand response by air-conditioning systems in a microgrid with considering wind power generation variation. In Proceedings of IEEE Innovative Smart Grid Technologies Asia. Tianjin, China, pp. 1-6.

Saldanha, N., Beausoleil-Morrison, I. (2012). Measured end-use electric load profiles for 12 Canadian houses at high temporal resolution. *Energy and Buildings.* Vol. 49, pp. 519-530.

Shimoda, Y., Asahi, T., Taniguchi, A., Mizuno, M., (2006). Evaluation of city-scale impact of residential energy conservation measures using the detailed end-use simulation model. *Energy.* Vol. 32(9), pp. 1617-1633.

Six, D., Desmedt, J., Johan, B., Vanhoudt, D. (2011). Exploring the Flexibility Potential of Residential Heat Pumps Combined with Thermal Energy Storage for Smart Grids. In: Proceedings of the 21st International Conference on Electricity Distribution, 6–9. Frankfurt.

Silva, V. (2010) Value of exibility in systems with large wind penetration. Electric power. Phd. Imperial College London

Snijders, T.A.B (1996). Stochastic actor-oriented models for network change. *Journal of Mathematical Sociology.* Vol. 21, pp. 149-172.

Spence, A., Demski, C., Butler, C., Parkhill, K. and Pidgeon, N. (2015). Public perceptions of demand-side management and a smarter energy future. *Nature Climate Change*. Vol 5. pp. 550–554.

Stadler, M., Krause. W., Sonnenschein, M., Vogel, U. (2007), The Adaptive Fridge – Comparing different control schemes for enhancing load shifting of electricity demand. In: Proceedings of the 21th Conference on informatics for Environmental Protection- Enviroinfo, Warsaw, Poland, pp. 199–206.

Starke, M., Alkadi, N., Oak Ridge National Laboratory (2013). Assessment of Industrial Load for Demand Response across U.S. Regions of the Western Interconnect. Available from: http://goo.gl/Hhvqew. Accessed on the 1st June 2014.

Stokes, M. (2005). *Removing barriers to embedded generation: a fine-grained load model to support low voltage network performance analysis.* PhD, De Montfort University.

Strbac, G., Gan, C.K., Aunedi, M., Stanojevic, V., Djapic, P., Dejvises, Pierluigi, M., Hawkes, A., Pudjianto, D. (2010). Benefits of Advanced Smart Metering for Demand Response based Control of Distribution Networks.

Suzenski, D.A. (2012). Price Response in Connecticut Light & Power's Variable Peak Pricing Option. PhD. Duke University

Swan, L. G., Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modelling techniques. *Renewable and Sustainable Energy Reviews*. Vol. 13, pp. 1819–1835.

Schweiker M., Haldi F., Shukuya M., Robinson D. 2012. "Verification of stochastic models of window opening behaviour for residential buildings." Journal of Building Performance Simulation. 5 (1): 55-74.

Tabak V., de Vries B. (2010). Methods for the prediction of intermediate activities by office occupants. *Building and Environment.* Vol 45(6), pp. 1366-1372.

Tanimoto, J., Hagishima, A., Sagara, H. (2006), A methodology for peak energy requirement considering actual variation of occupants' behavior schedules. *Building and Environment.* Vol. 43(4), pp. 610-619.

Tanimoto, J., Hagishima, A. Sagara, H. (2008). A methodology for peak energy requirement considering actual variation of occupants' behavior schedules. *Building and Environment*. Vol. 43, pp. 610–619.

Tanimoto, J., Hagishima, A. (2010). Total utility demand prediction system for dwellings based on stochastic processes of actual inhabitants. *Journal of Building Performance Simulation.* Vol. 3(2), pp. 155-167.

Tiwari, P. (2000). Architectural, demographic, and economic causes of electricity consumption in Bombay. *Journal of Policy Modeling*, Vol. 22(1), pp. 81–98.

The Scottish Government (2013). Electricity Generation Policy Statement. Available from: http://www.scotland.gov.uk/Publications/2013/06/5757. Accessed on the 3rd July 2014.

THINK Project (2013), Shift, Not Drift: Towards Active Demand Response and Beyond. Available from: http://goo.gl/rJMBk8. Accessed on the 5th May 2014.

Thomson, M., Infield, D.G. (2007). Network Power-Flow Analysis for a High Penetration of Distributed Generation. *IEEE Transactions on Power Systems.* Vol. 22(3), pp. 1157-1162.

Torriti, J., Hassan, M.G., Leach, M. (2010). Demand response experience in Europe: Policies, programmes and implementation. *Energy.* Vol. 35(4), pp. 1575-1583.

Torriti, J. (2011). The elasticity of demand is about occupancy, not prices: building European demand curves based on occupancy elasticity. In: Proceedings of UKERC 1st Conference of Energy and People, Oxford, United Kingdom.

UKERC (2013). The UK energy system in 2050: Comparing Low-Carbon, Resilient Scenarios. UK Energy Research Centre. Available from: http://discovery.ucl.ac.uk/1396496/. Accessed on the 5th January 2014.

UKERC (2014). Scenarios for the Development of Smart Grids in the UK. Synthesis Report. UK Energy Research Centre. Available from: http://goo.gl/AWZt8z. Accessed on 27th February 2014.

US DOE (2006). Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them: A Report to the United States Congress Pursuant to Section 1252 Of The Energy Policy Act of 2005. Available from: http://goo.gl/kyHs2k. Accessed on the 10th February 2014.

Walker, C.F., Pokoski, J.L. (1985). Residential load shape modeling based on customer behavior. *IEEE Transaction on Power Apparatus and Systems.* Vol. 104(7), pp. 1703–1711.

Widén, J., Lundh, M., Vassileva, I., Dahiquist, E., Ellegard, K., Wäckelgård, E. (2009). Constructing load profiles for household electricity and hot water from time-use data. Modelling approach and validation. *Energy and Buildings*. Vol. 41(7), pp. 753–768.

Widén, J., Karlsson, B. 2010. "End-user value of on-site domestic photovoltaic generation with different metering options in Sweden." Paper presented at the 8th EuroSun conference of ISES Europe, Graz, October 28-November 01.

Widén, J., Wäckelgård, E. (2010). A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*. Vol. 87, pp. 1880–1892.

Widén, J., Molin, A., Ellegård, K. (2011). Models of domestic occupancy, activities and energy use based on time-use data: deterministic and stochastic approaches with application to various building-related simulations. *Journal of Building Performance Simulation.* Vol. 5(1), pp.27-44.

Widén, J., Molin, A., Ellegård, K. (2012). Models of domestic occupancy, activities and energy use based on time-use data: deterministic and stochastic approaches with application to various building-related simulations. *Journal of Building Performance Simulation.* Vol. 5(1), pp. 27-44.

Wiesmann, D., Lima Azevedo, I., Ferrão, P., & Fernández, J. E. (2011). Residential electricity consumption in Portugal: Findings from top-down and bottom-up models. *Energy Policy*. Vol. 39(5), pp. 2772–2779.

Wilke, U. (2013). Probabilistic Bottom-up Modelling of Occupancy and Activities to Predict Electricity Demand in Residential Buildings. PhD, École Polytechnique de Fédérale Lausanne.

Wilké, U., Haldi, F., Scartezzini, J.L., Robinson, D. (2013). A bottom-up stochastic model to predict building occupants' time-dependent activities. *Building and Environment.* Vol. 60, pp. 254-264.

Wright, A., Firth, S. (2007). The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations. *Applied Energy*. Vol. 84(4), pp. 389-403.

Yamaguchi, Y., Fujimoto, T., Shimoda, Y. 2011. "Occupant behavior model for households to estimate high-temporal resolution residential electricity demand profile." Paper presented at the 12th Conference of International Building Performance Simulation Association, Sydney, November 14-16.

Yan, D., Hong, T. 2014. "Definition and Simulation of Occupant Behavior in Buildings" International Energy Agency EBC Annex 66 Text: 1-14.

Yang, J., Rivard, H., Zmeureanu, R. (2005). Building energy prediction with adaptive artificial neural networks. In: Proceedings of the 9th IBPSA Conference, Montreal, Canada, pp. 1401–1408.

Yao, R., Steemers, K. (2005). A method of formulating energy load profile for domestic buildings in the UK. *Energy and Buildings.* Vol. 37(6), pp. 663–671.

Yu, T., Kim, D.S., Son, S.Y. (2013). Optimization of Scheduling for Home Appliances in Conjunction with Renewable and Energy Storage Resources. *International Journal of Smart Home.* Vol. 7(4), pp. 1-5.

Yohanis, Y. G., Mondol, J. D., Wright, A., & Norton, B. (2008). Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. *Energy and Buildings.* Vol 40(6), pp. 1053–1059.

Zhang, W. Lian, W., Chang, C.Y., Kalsi, K. (2013). Aggregated Modeling and Control of Air Conditioning Loads for Demand Response. IEEET Transactions on Power Systems, Vol. 28(4), pp. 4655-4664.

Zhou, S. & Teng, F. (2013). Estimation of urban residential electricity demand in China using household survey data. *Energy Policy*. Vol. 61, pp. 394-402.

Zhu, Z., Tang, J., Lambotharan, S., Chin, W.H, Fan, Z. (2012), An integer linear programming based optimization for home demand-side management in smart grid. In: Proceedings of IEEE PES Innovative Smart Grid Technologies (ISGT), Washington, DC, United States.

10 APPENDICES

10.1 APPENDIX A

This appendix provides additional detail on the Levene's test and ANOVA run for Section 4.2.1 to test effect of household types, occupant numbers, day types and seasons on the average daily number of switch-on events. Secondly, Levene's test and ANOVA run for Section 4.2.3 to test effect of the time-slot of the day on the duration of the activities.

Table 10.1 shows the results of the one-way ANOVA. First of all, Levene's test is performed to test the homogeneity of variances. p-values are shown for the Levene's test is presented. If the p-values of the Levene's test is less than 0.05, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. Therefore, for these appliance groups, the ANOVA is not performed as it violates one of the assumption of ANOVA (Section 3.2). For appliances, which have p-value higher than 0.05, one-way ANOVA test is performed. For dishwashers, the ANOVA test results show that there is a significant effect of household type on the average daily number of switch-on events at the $p<0.05$ [$F(2,86)=5.312$, $p=0.001$]. Similarly, the ANOVA test results show that there is a significant effect of occupant number on the average daily number of switch-on events at the $p<0.05$ [$F(2,86)=6.091$, $p=0.000$]. For upright-freezers, the ANOVA test results show that there is a significant effect of occupant number on the average daily number of switch-on events at the $p<0.05$ [$F(2,86)=3.615$, $p=0.006$]. For rest of the appliances, ANOVA results show that there is not a significant effect of household types, occupant numbers and day types on the average daily number of switch-on events.

Table 10.1 One-way ANOVA test results: p-value of Levene's test for hypothesis of equal variance; p-value of ANOVA test and F-value if the test is significant <0.05

Appliances	Levene's test p-value of 0.05	ANOVA test p-value of 0.05 (F value if meaningful)

Appliance category	Appliance Types	Household type	Occupant number	Day type	Household type	Occupant number	Day type
Wet appliances	**Washing machine**	0.008	0.02	0.008	-	-	-
	Washing-drying machine	0.566	0.001	0.386	0.920	-	0.763
	Tumble dryer	0.193	0.167	0.769	0.191	0.182	0.723
	Dishwasher	0.490	0.935	1.000	p=0.001 F=5.312	p=0.000 F=6.091	1.000
Cooking appliances	**Cooker**	0.015	0.456	0.908	-	0.643	0.096
	Oven	0.134	0.180	0.960	0.138	0.184	0.995
	Hob	0.057	0.314	0.999	0.668	0.565	0.992
	Grill	0.176	-*	0.044	0.361	-	-
Televisions	**TV1**	0.678	0.915	0.000	0.559	0.673	-
	TV2	0.385	0.619	0.276	0.942	0.900	0.743
	TV3	0.136	0.013	0.826	0.407	-	0.909
Electric shower		0.001	0.218	0.898	-	0.133	0.996
Cold Appliances	**Fridge**	0.784	0.503	0.955	0.740	0.641	0.984
	Fridge freezer	0.515	0.247	1.000	0.580	0.770	1.000
	Chest freezer	0.001	0.031	1.000	-	-	-
	Upright freezer	0.286	0.090	1.000	0.588	p=0.006 F=3.615	1.000

*Levene test cannot be Test of homogeneity of variances cannot be performed for frequency because the sum of case weights is less than the number of groups.

A one-way ANOVA test was conducted to compare the effect of season on the mean of average daily number of switch-on events. Table 10.2 shows the results of the one-way ANOVA. First of all, Levene's test is performed to test the homogeneity of variances. p-values are shown for the Levene's test is presented. If the p-values of the Levene's test is less than 0.05, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. Therefore, grills, the ANOVA is not performed as it violates one of the assumption of ANOVA (Section 3.2). For the rest of the appliances, which have p-value higher than 0.05, one-way ANOVA test is performed. Only for washing machines, the ANOVA test results show that there is a significant effect of seasonality on the average daily number of switch-on events at the $p<0.05$ [$F(2,327)=2.983$, $p=0.031$]. For rest of the appliances, the ANOVA test results show that there is a not significant effect of seasonality on the average daily number of switch-on events at the $p<0.05$.

Table 10.2 One-way ANOVA test results: p-value of Levene's test for hypothesis of equal variance; p-value of ANOVA test and F-value if the test is significant <0.05

Appliance category	Appliance Types	Levene's test p-value	ANOVA test p-value of 0.05 (F value if meaningful)

Wet appliances	**Washing machine**	0.409	p=0.031 F=2.983
	Washing-drying machine	0.553	0.924
	Tumble dryer	0.251	0.083
	Dishwasher	0.596	0.307
Cooking appliances	**Cooker**	0.002	-
	Oven	0.572	0.939
	Hob	0.338	0.254
	Grill	0.099	0.823
Televisions	**TV1**	0.315	0.212
	TV2	0.056	0.554
Electric shower		0.813	0.645
Cold Appliances	**Fridge**	0.420	0.160
	Fridge freezer	0.364	0.163
	Chest freezer	0.572	0.982
	Upright freezer	0.825	0.849

A one-way ANOVA test was conducted to compare the effect of time slot on the mean of mean duration of the appliance operation. Table 10.3 shows the results of the one-way ANOVA. First of all, Levene's test is performed to test the homogeneity of variances. p-values are shown for the Levene's test is presented. If the p-values of the Levene's test is less than 0.05, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population.

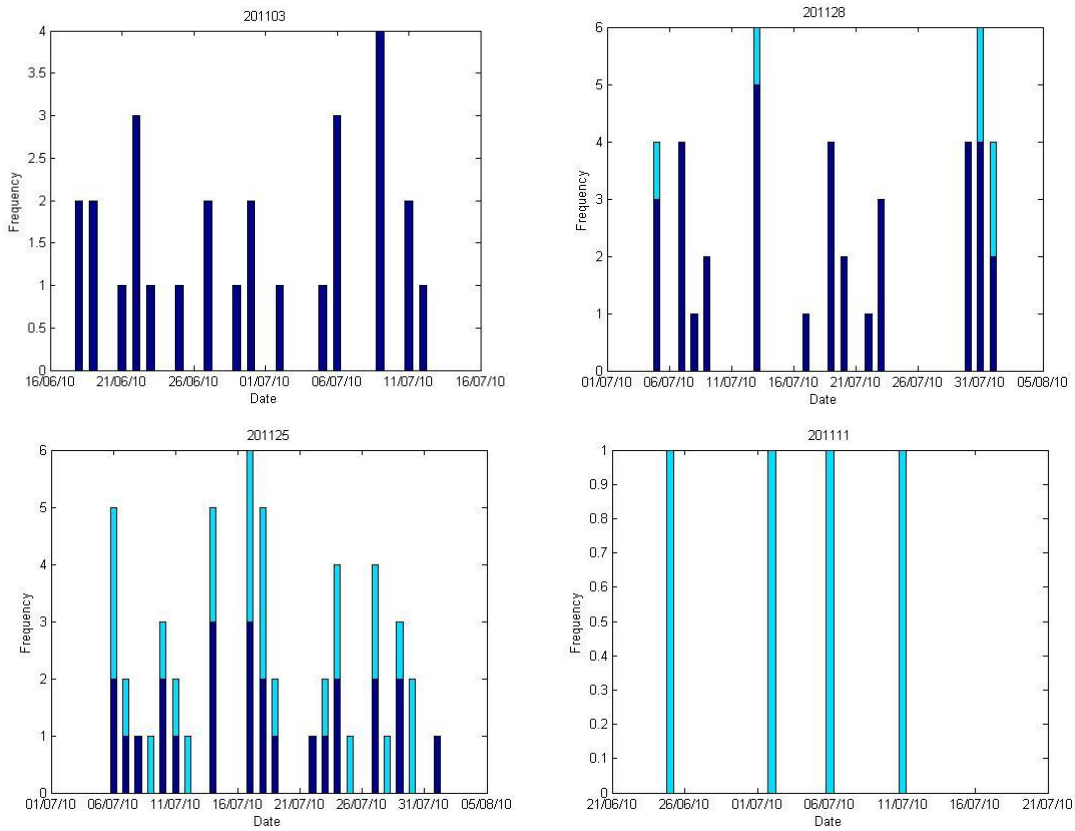
Only for cooking appliances and televisions, the ANOVA test results show that there is a significant effect of time slot the appliance is switched-on on the duration of the length of the appliance use. For rest of the appliances, the ANOVA test results show that there is a not significant effect of time slot the appliance is switched-on on the duration of the length of the appliance use at the $p<0.05$.

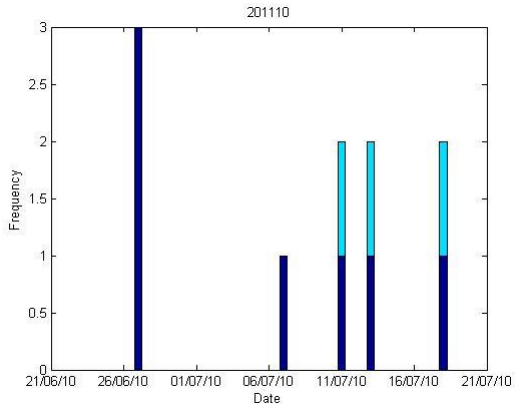
Table 10.3 One-way ANOVA test results: p-value of Levene's test for hypothesis of equal variance; p-value of ANOVA test and F-value if the test is significant <0.05

Appliance category	Appliance Types	Levene's test p-value	ANOVA test p-value of 0.05 (F value if meaningful)
	Washing machine	0.527	0.613

Wet appliances	**Washing-drying machine**	0.623	0.722
	Tumble dryer	0.312	0.183
	Dishwasher	0.456	0.412
Cooking appliances	**Cooker**	0.213	p=0.012 F=3.134
	Oven	0.419	p=0.041 F=4.111
	Hob	0.333	p=0.011 F=2.443
	Grill	0.120	p=0.033 F=1.946
Televisions	**TV1**	0.122	p=0.021 F=4.433
	TV2	0.612	p=0.041 F=3.961
	TV3	0.731	p=0.011 F=3.121
Electric shower		0.813	0.645
Cold Appliances	**Fridge**	0.420	0.160
	Fridge freezer	0.364	0.163
	Chest freezer	0.572	0.982
	Upright freezer	0.825	0.849

Number of switch-on events

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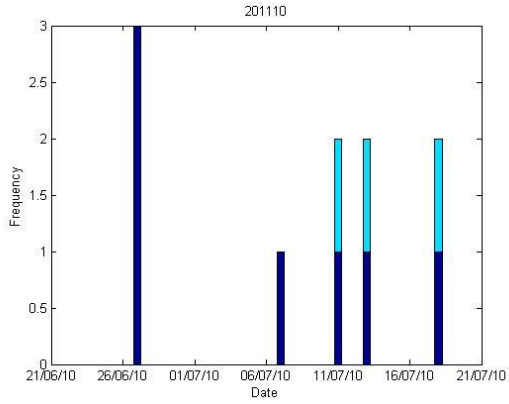
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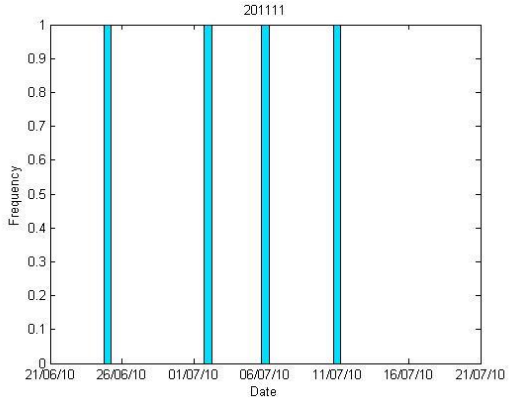
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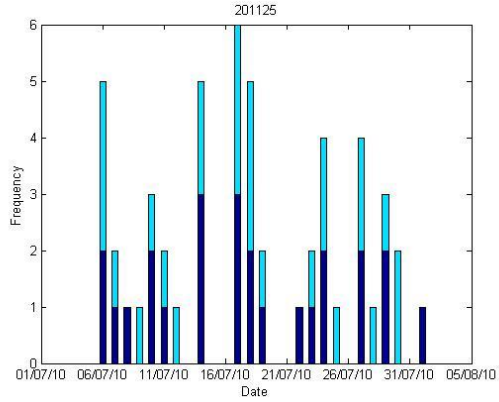
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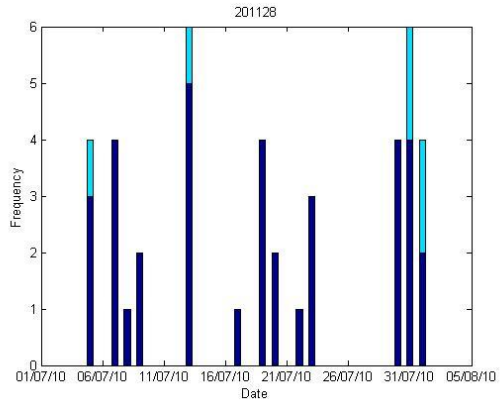
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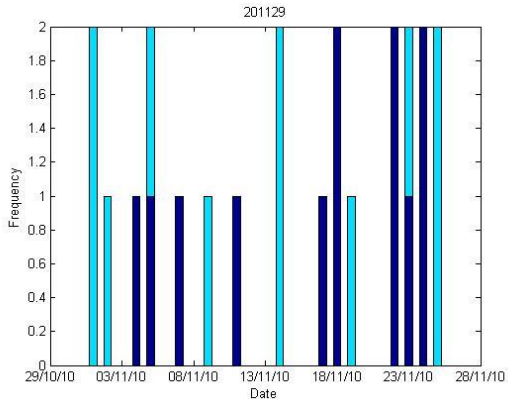
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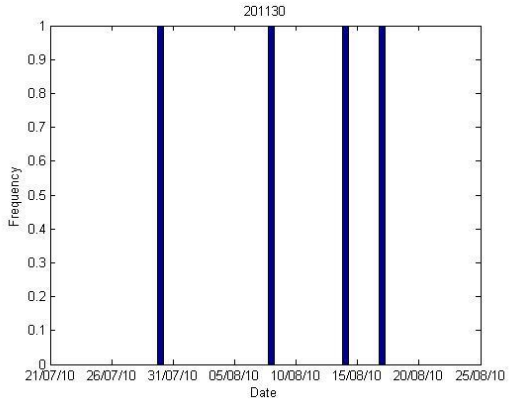
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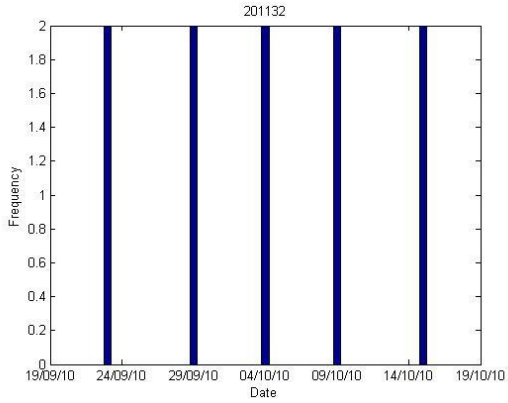
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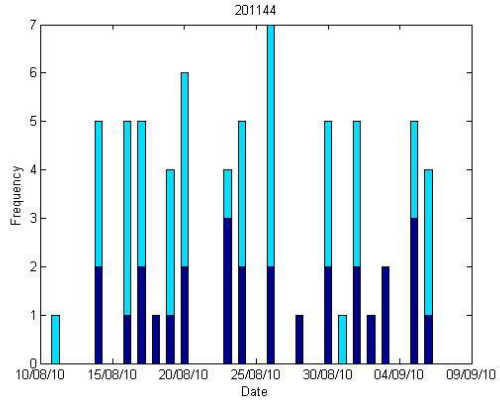
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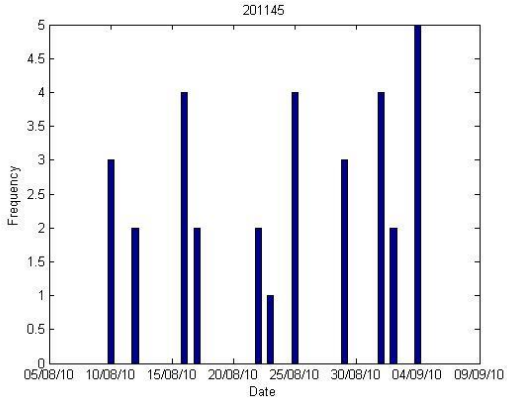
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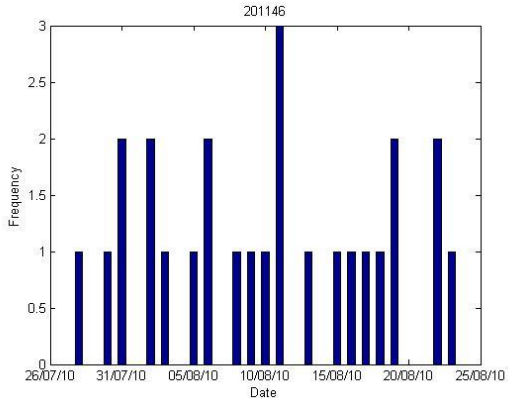
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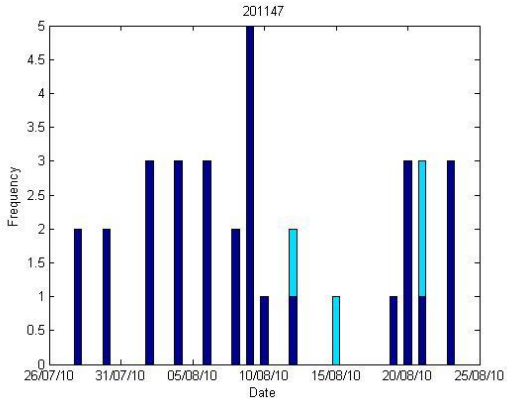
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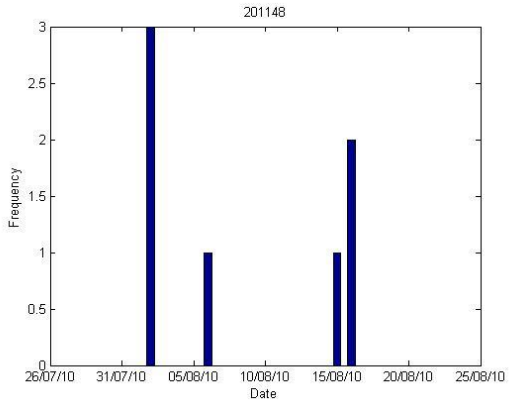
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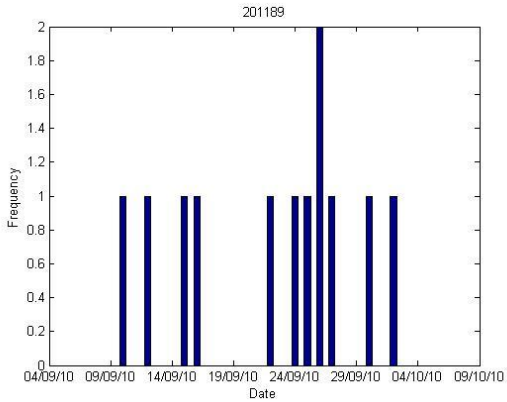
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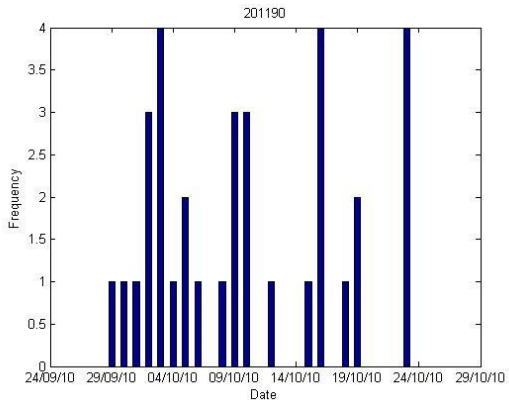
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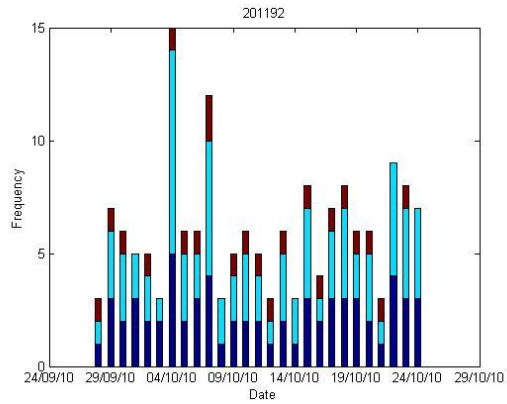
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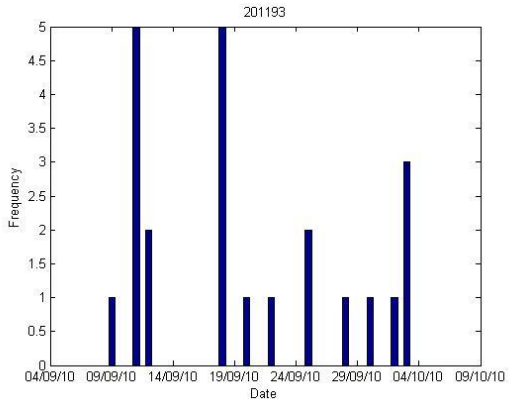
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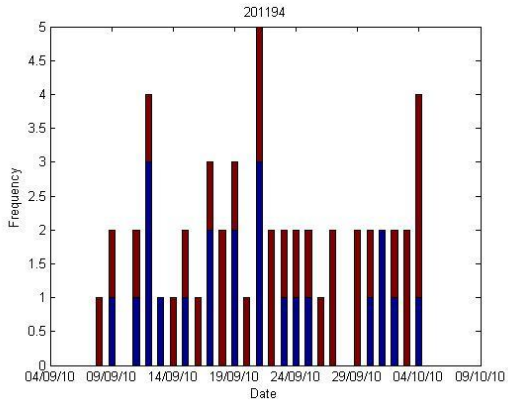
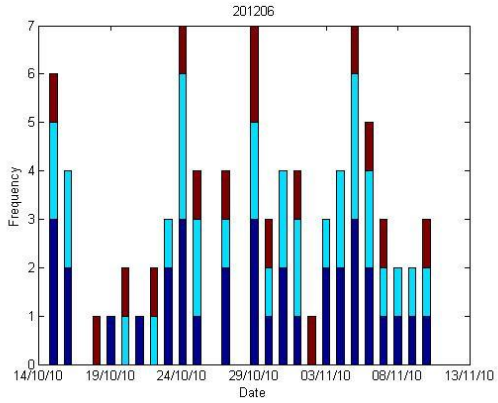
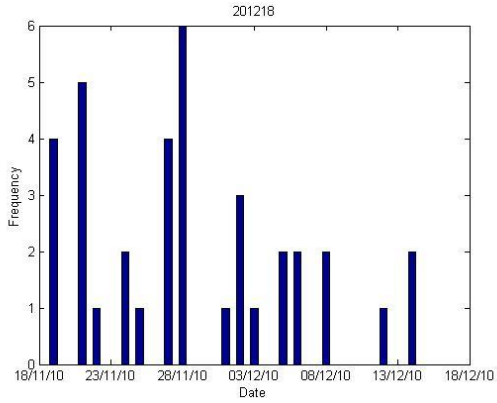
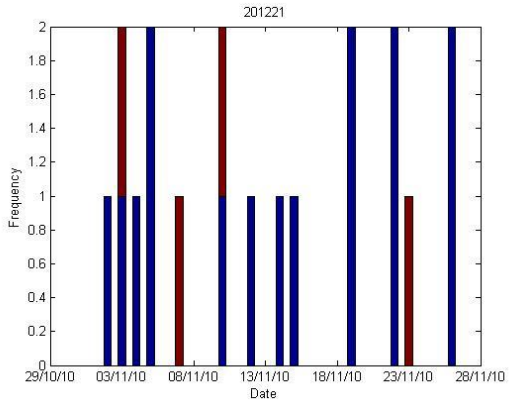
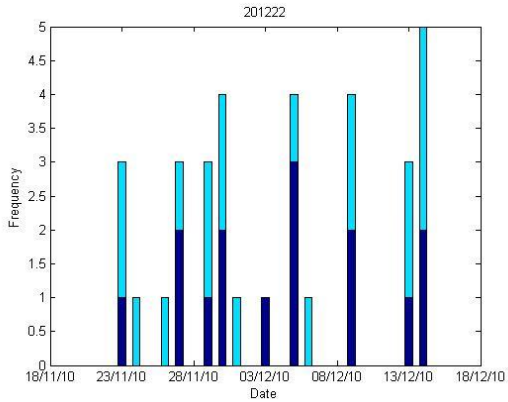
04/09/10 09/09/10 14/09/10 19/09/10 24/09/10 29/09/10 04/10/10 09/10/10

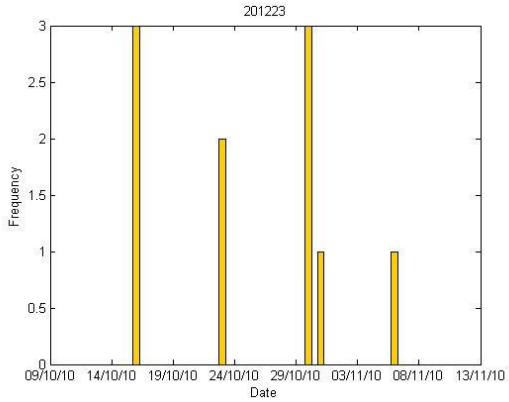

201194
Frequency
Date
04/09/10 09/09/10 14/09/10 19/09/10 24/09/10 29/09/10 04/10/10 09/10/10

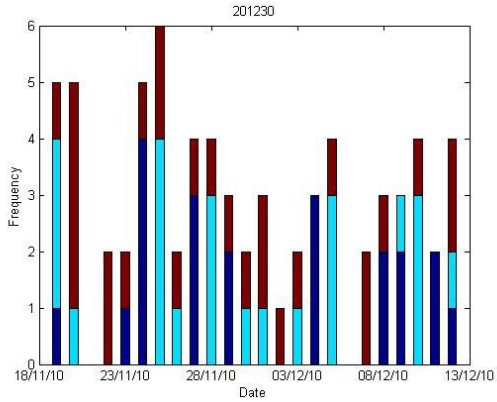

201206
Frequency
Date
14/10/10 19/10/10 24/10/10 29/10/10 03/11/10 08/11/10 13/11/10

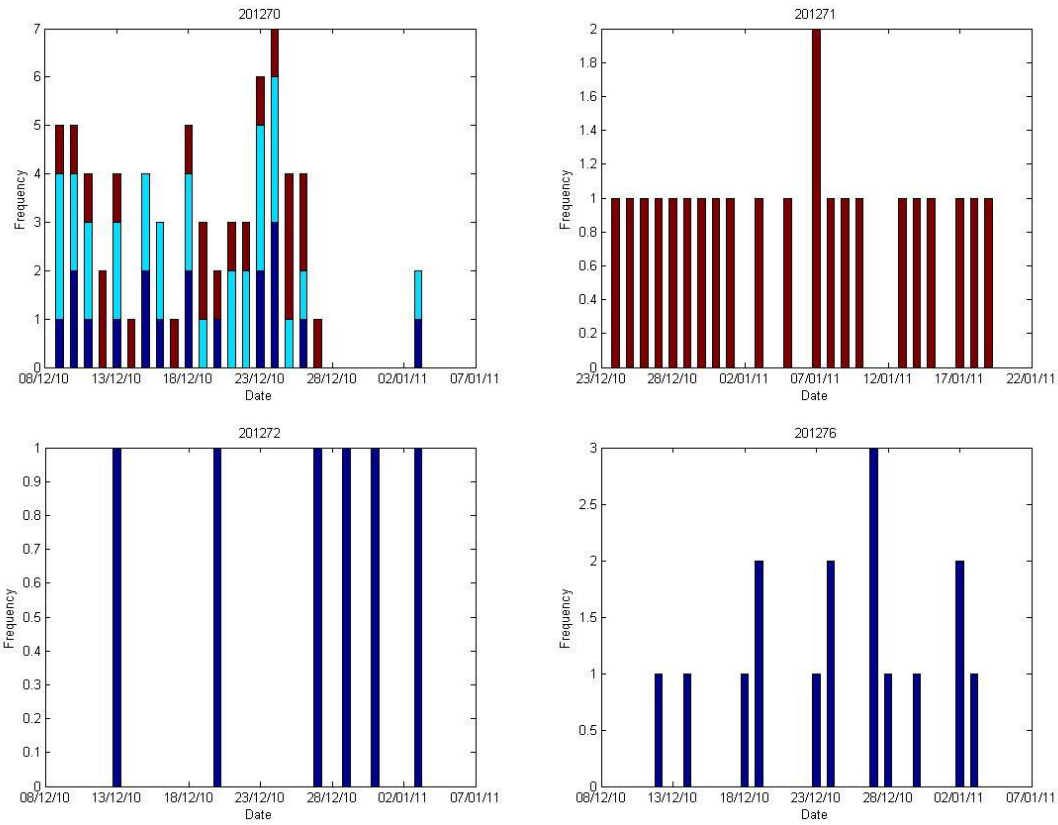

201218
Frequency
Date
18/11/10 23/11/10 28/11/10 03/12/10 08/12/10 13/12/10 18/12/10


201221
Frequency
Date
29/10/10 03/11/10 08/11/10 13/11/10 18/11/10 23/11/10 28/11/10


201222
Frequency
Date
18/11/10 23/11/10 28/11/10 03/12/10 08/12/10 13/12/10 18/12/10

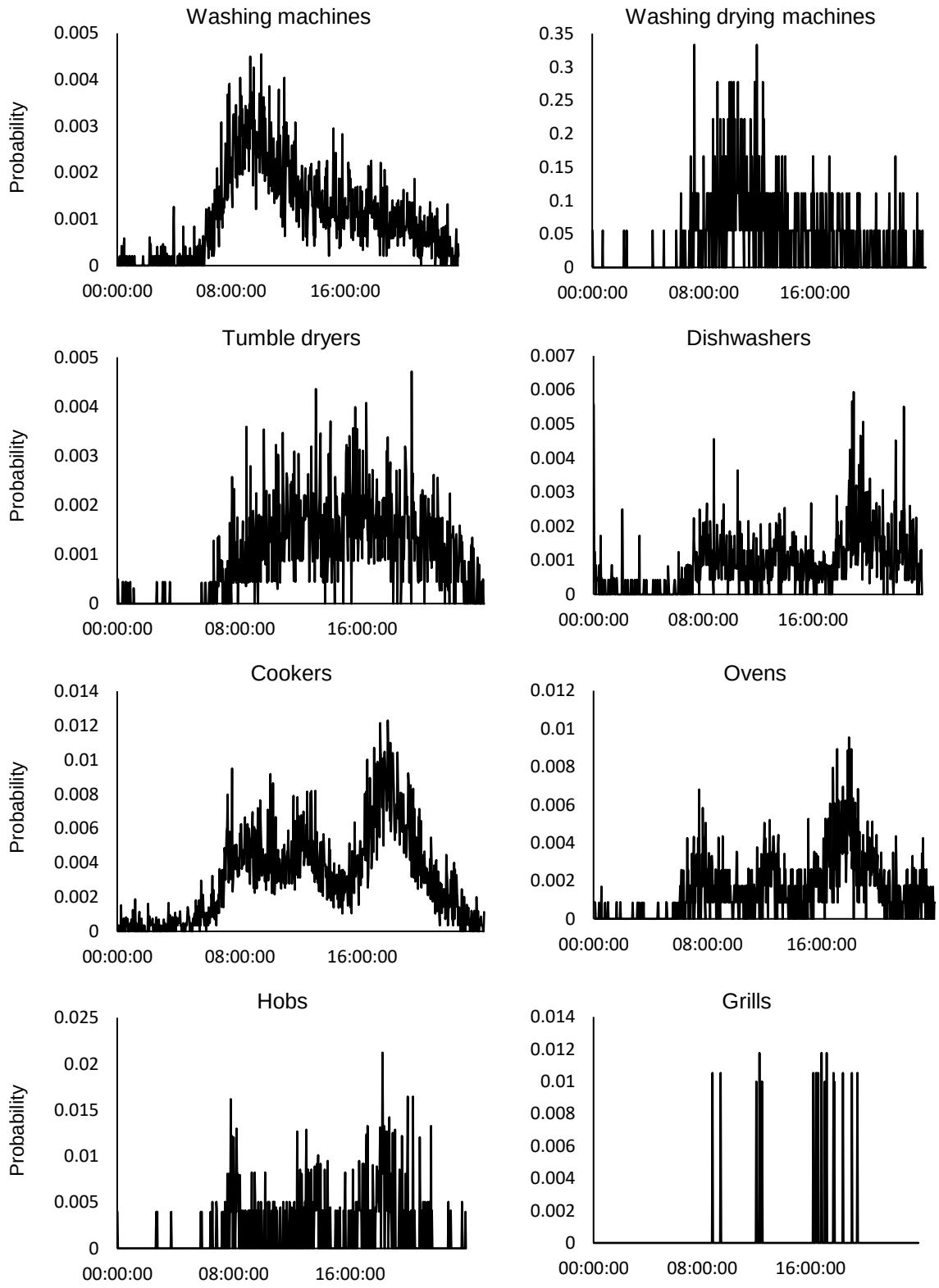

201223
Frequency
Date
09/10/10 14/10/10 19/10/10 24/10/10 29/10/10 03/11/10 08/11/10 13/11/10


201230
Frequency
Date
18/11/10 23/11/10 28/11/10 03/12/10 08/12/10 13/12/10


201270
Frequency
Date
08/12/10
13/12/10
18/12/10
23/12/10
28/12/10
02/01/11
07/01/11
201271
Frequency
Date
23/12/10
28/12/10
02/01/11
07/01/11
12/01/11
17/01/11
22/01/11
201272
Frequency
Date
08/12/10
13/12/10
18/12/10
23/12/10
28/12/10
02/01/11
07/01/11
201276
Frequency
Date
08/12/10
13/12/10
18/12/10
23/12/10
28/12/10
02/01/11
07/01/11

10.2 APPENDIX B

This appendix provides additional detail on the average 2-minutely switch-on probabilities of the 16 appliance types.



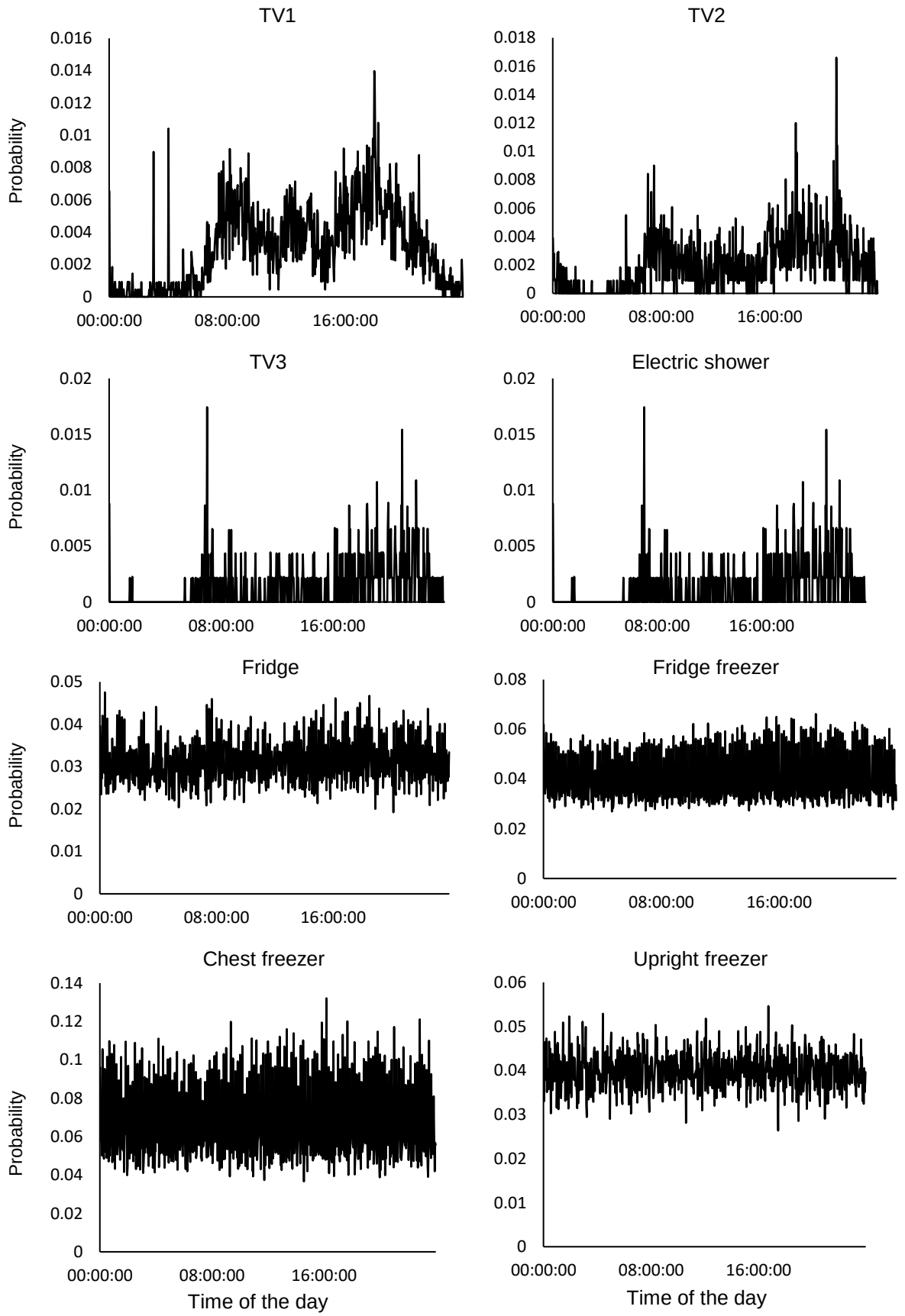
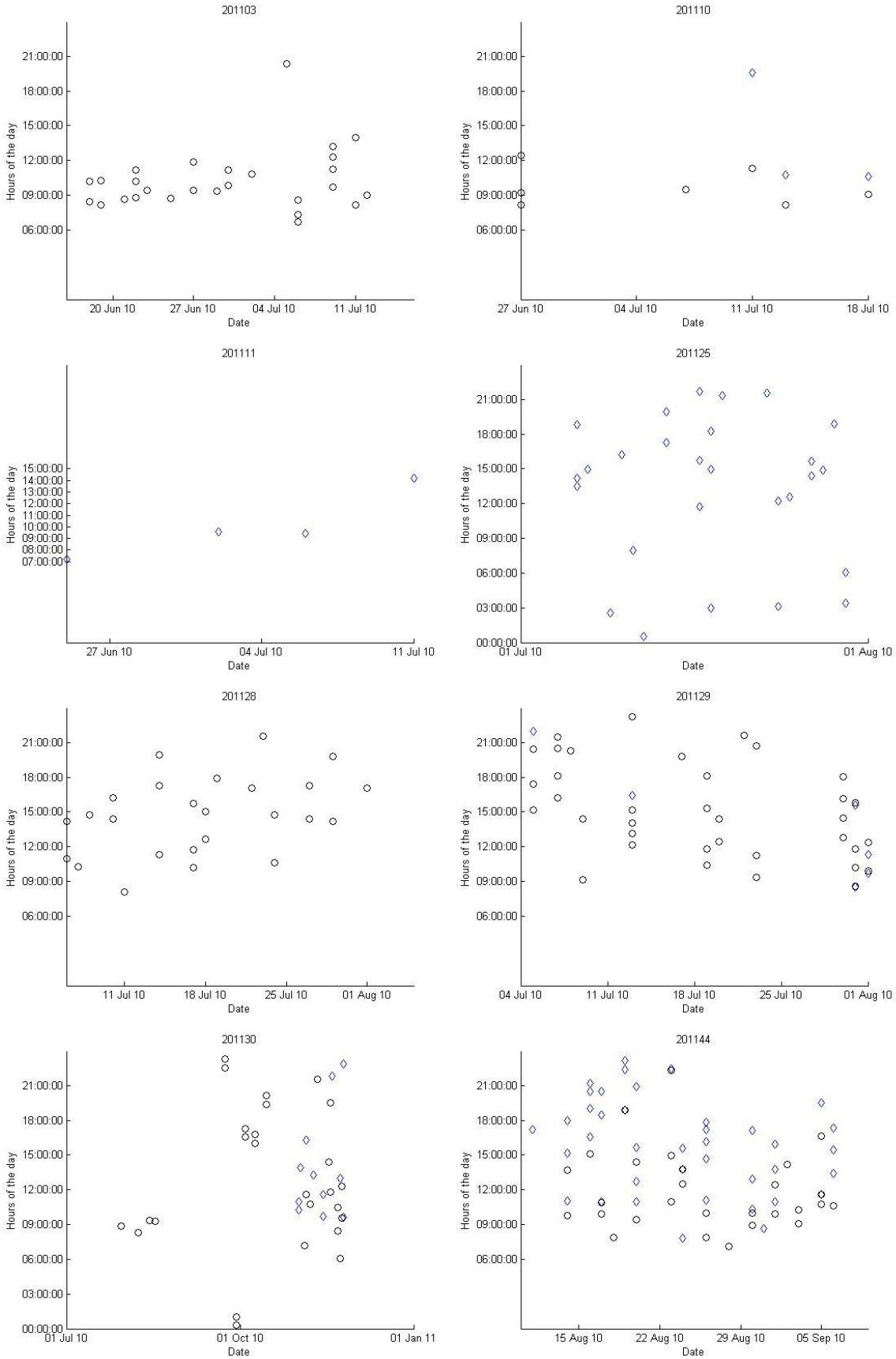
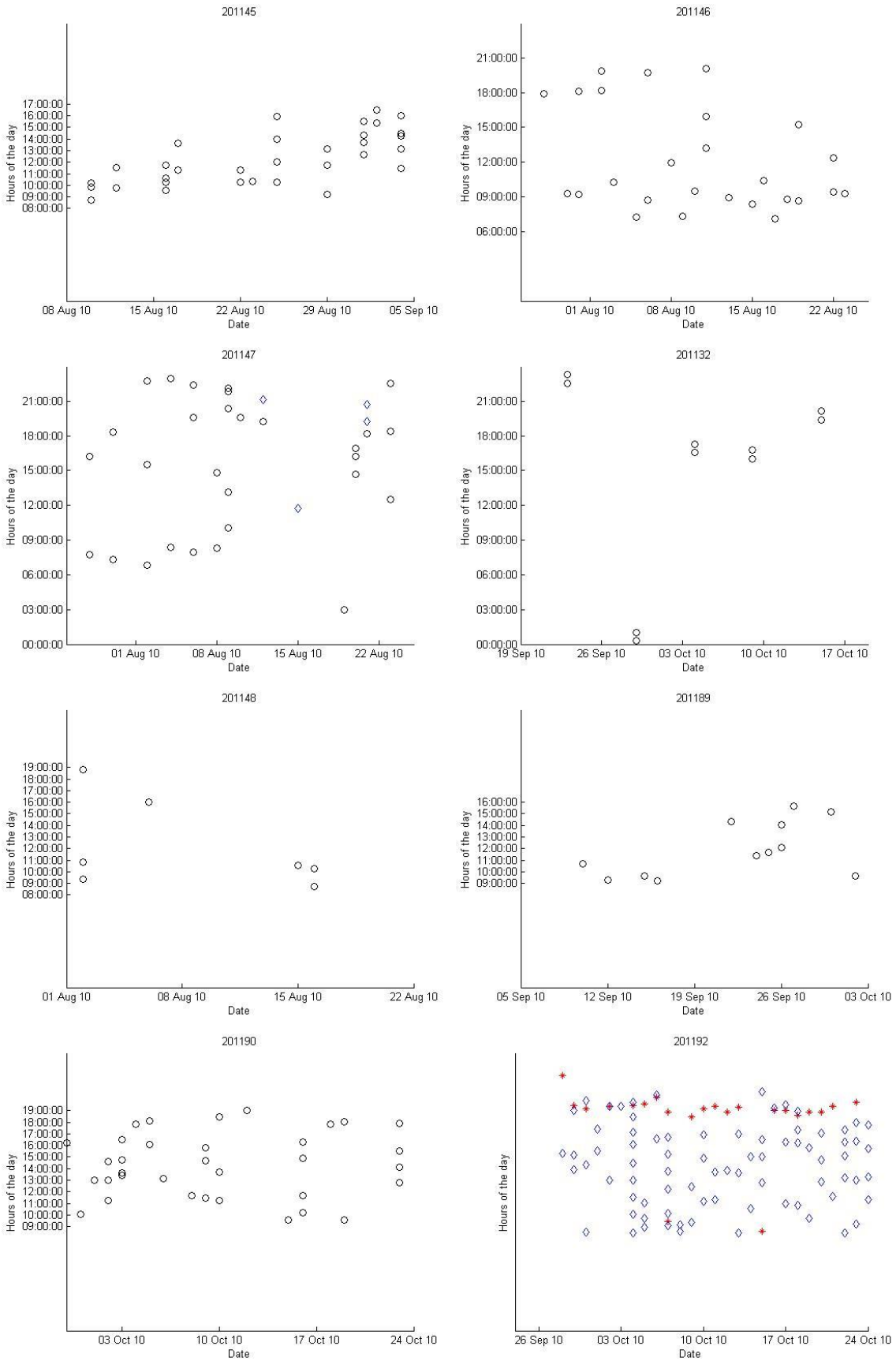
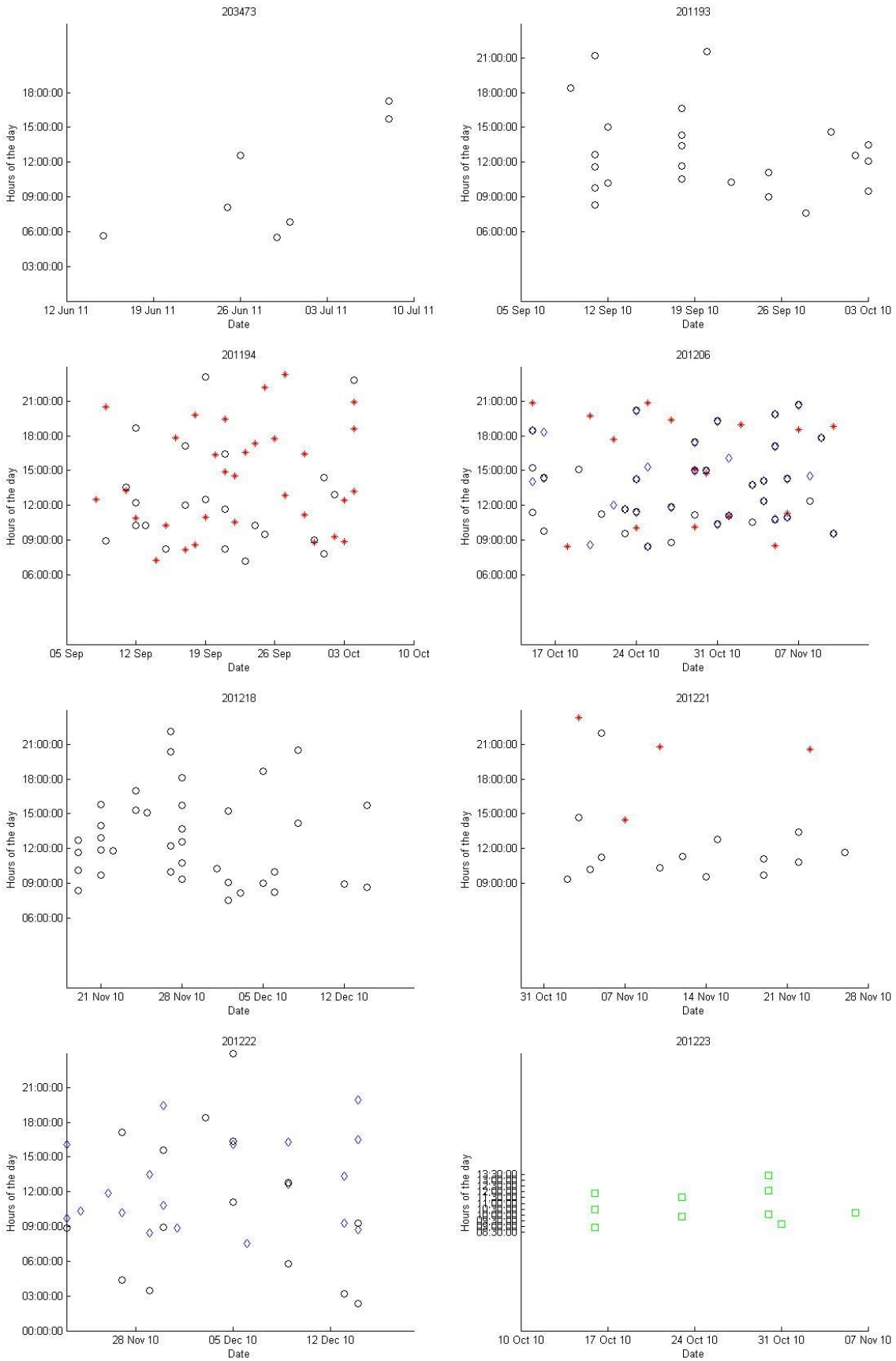


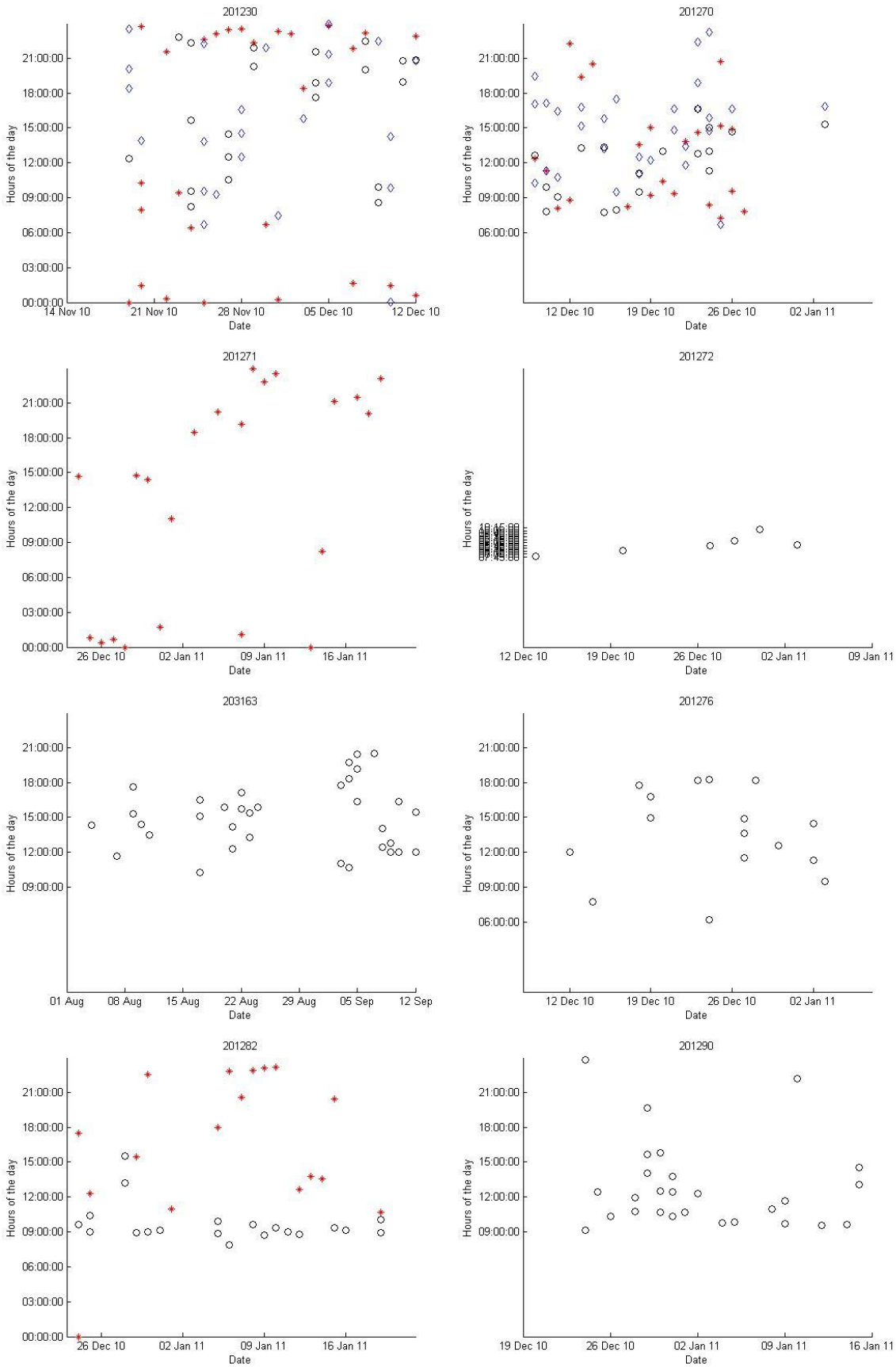
Figure 10.1 Average 2-minutely switch-on probabilities of 16 appliance types

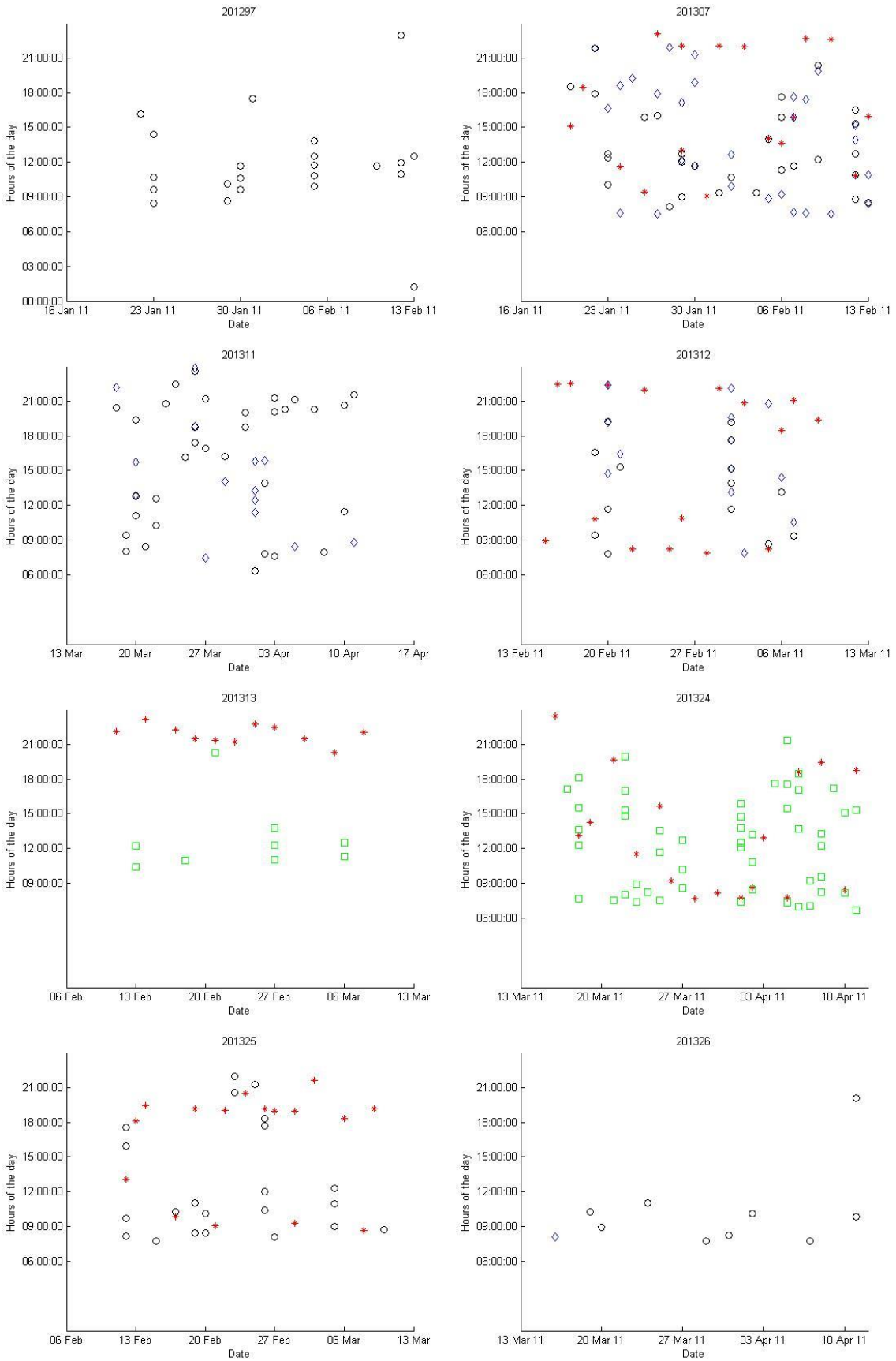
Distribution of start-times of wet appliances for several households




201145
Hours of the day
17:00:00
16:00:00
15:00:00
14:00:00
13:00:00
12:00:00
11:00:00
10:00:00
09:00:00
08:00:00
08 Aug 10
15 Aug 10
22 Aug 10
29 Aug 10
05 Sep 10
Date
201146
Hours of the day
21:00:00
18:00:00
15:00:00
12:00:00
09:00:00
06:00:00
01 Aug 10
08 Aug 10
15 Aug 10
22 Aug 10
Date
201147
Hours of the day
21:00:00
18:00:00
15:00:00
12:00:00
09:00:00
06:00:00
03:00:00
00:00:00
01 Aug 10
08 Aug 10
15 Aug 10
22 Aug 10
Date
201132
Hours of the day
21:00:00
18:00:00
15:00:00
12:00:00
09:00:00
06:00:00
03:00:00
00:00:00
19 Sep 10
26 Sep 10
03 Oct 10
10 Oct 10
17 Oct 10
Date
201148
Hours of the day
19:00:00
18:00:00
17:00:00
16:00:00
15:00:00
14:00:00
13:00:00
12:00:00
11:00:00
10:00:00
09:00:00
08:00:00
01 Aug 10
08 Aug 10
15 Aug 10
22 Aug 10
Date
201189
Hours of the day
16:00:00
15:00:00
14:00:00
13:00:00
12:00:00
11:00:00
10:00:00
09:00:00
05 Sep 10
12 Sep 10
19 Sep 10
26 Sep 10
03 Oct 10
Date
201190
Hours of the day
19:00:00
18:00:00
17:00:00
16:00:00
15:00:00
14:00:00
13:00:00
12:00:00
11:00:00
10:00:00
09:00:00
03 Oct 10
10 Oct 10
17 Oct 10
24 Oct 10
Date
201192
Hours of the day
26 Sep 10
03 Oct 10
10 Oct 10
17 Oct 10
24 Oct 10
Date


203473
201193
201194
201206
201218
201221
201222
201223
Hours of the day
Date
12 Jun 11
19 Jun 11
26 Jun 11
03 Jul 11
10 Jul 11
05 Sep 10
12 Sep 10
19 Sep 10
26 Sep 10
03 Oct 10
05 Sep
12 Sep
19 Sep
26 Sep
03 Oct
10 Oct
17 Oct 10
24 Oct 10
31 Oct 10
07 Nov 10
21 Nov 10
28 Nov 10
05 Dec 10
12 Dec 10
14 Nov 10
00:00:00
03:00:00
06:00:00
09:00:00
12:00:00
15:00:00
18:00:00
21:00:00

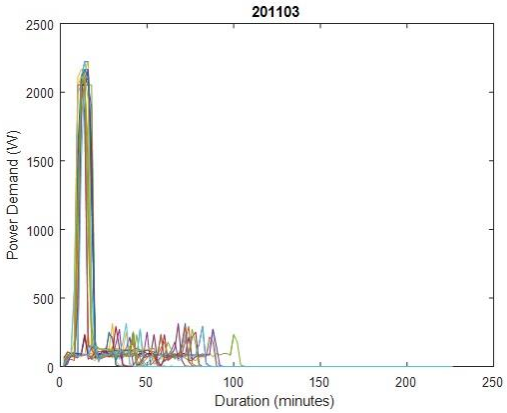

201230
Hours of the day
21:00:00
18:00:00
15:00:00
12:00:00
09:00:00
06:00:00
03:00:00
00:00:00
14 Nov 10
21 Nov 10
28 Nov 10
05 Dec 10
12 Dec 10
Date
201270
12 Dec 10
19 Dec 10
26 Dec 10
02 Jan 11
201271
26 Dec 10
02 Jan 11
09 Jan 11
16 Jan 11
201272
09 Jan 11
203163
01 Aug
08 Aug
15 Aug
22 Aug
29 Aug
05 Sep
12 Sep
201276
201282
201290
19 Dec 10

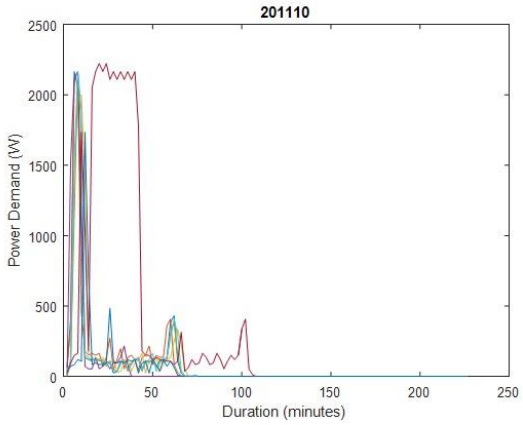

201297
201307
201311
201312
201313
201324
201325
201326
Hours of the day
Date
21:00:00
18:00:00
15:00:00
12:00:00
09:00:00
06:00:00
03:00:00
00:00:00
16 Jan 11
23 Jan 11
30 Jan 11
06 Feb 11
13 Feb 11
13 Mar
20 Mar
27 Mar
03 Apr
10 Apr
17 Apr
20 Feb 11
27 Feb 11
06 Mar 11
13 Mar 11
06 Feb
13 Feb
20 Feb
27 Feb
06 Mar
13 Mar
20 Mar 11
27 Mar 11
03 Apr 11
10 Apr 11

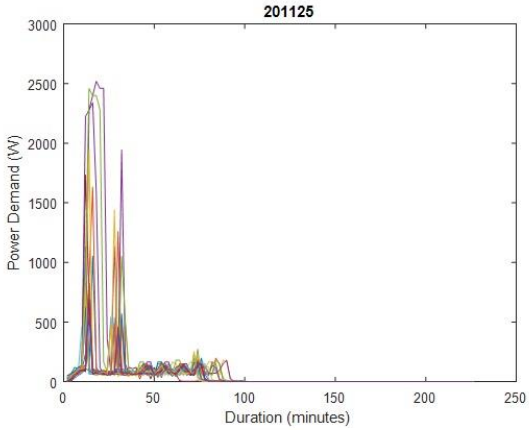
10.3 APPENDIX C

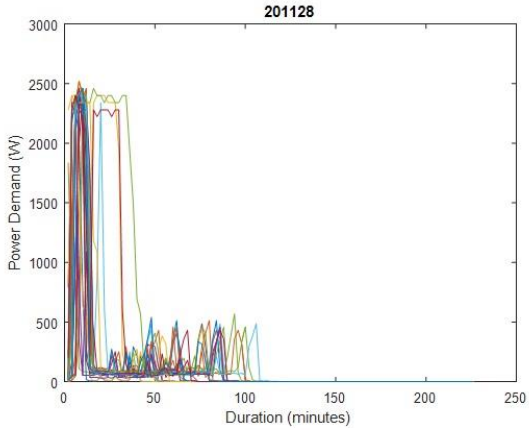
This section shows several examples of the power demand during usage for each household. Not all households are included as it would be more than 200 pages.

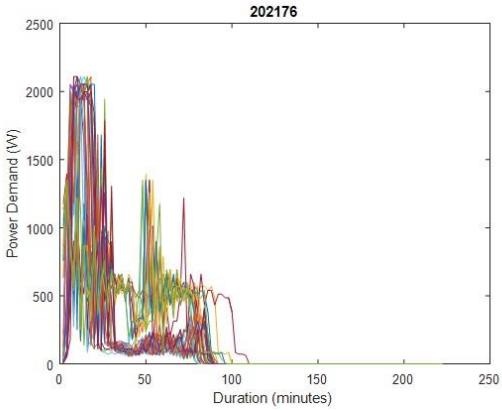
Washing machines

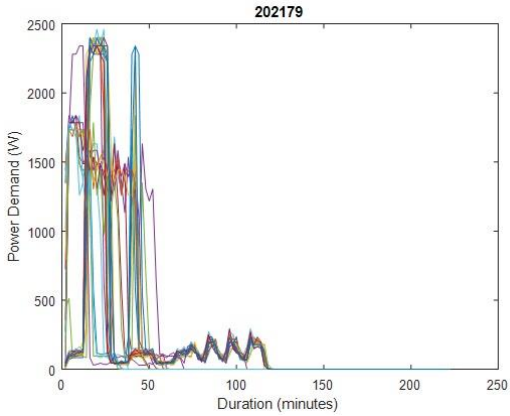


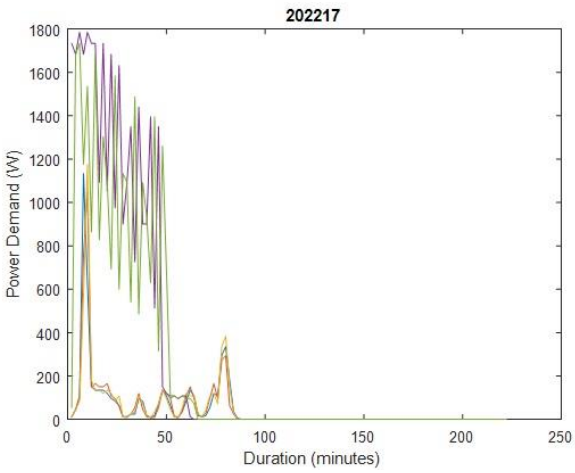


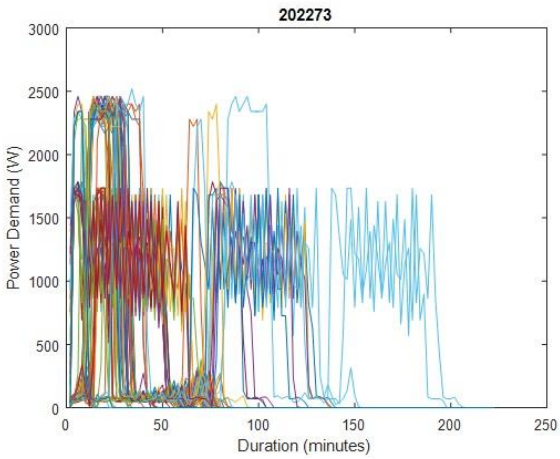


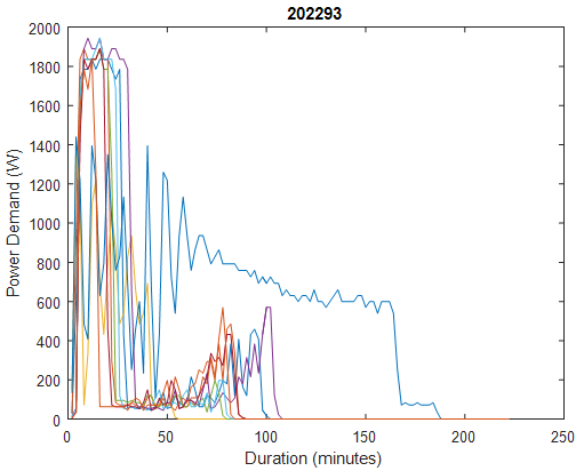


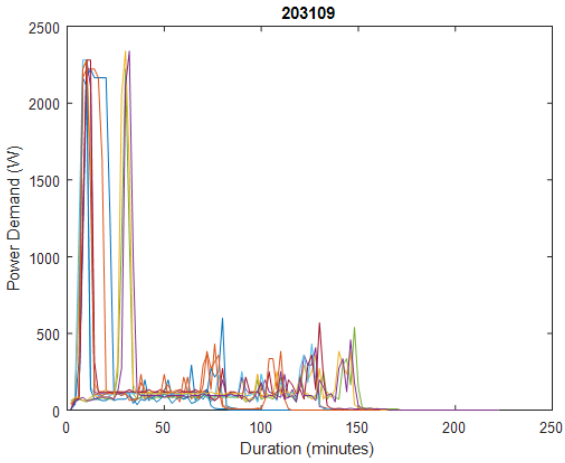


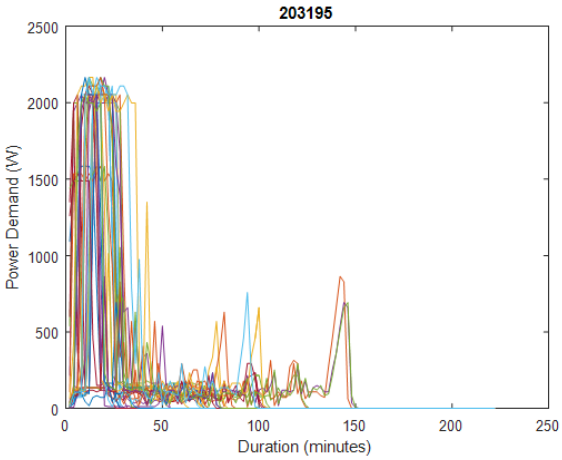


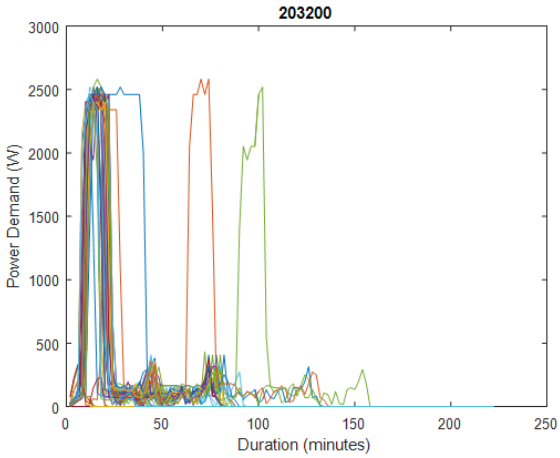

202217
Power Demand (W)
Duration (minutes)


202273
Power Demand (W)
Duration (minutes)

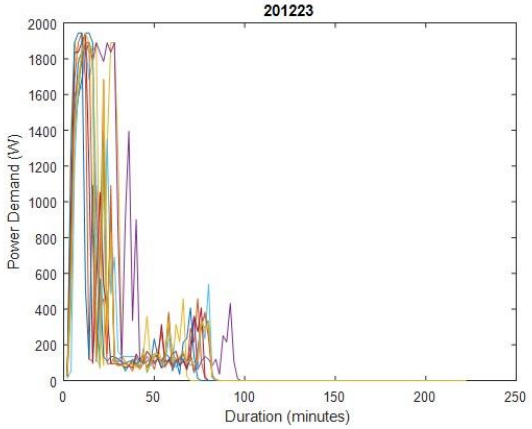

202293
Power Demand (W)
Duration (minutes)

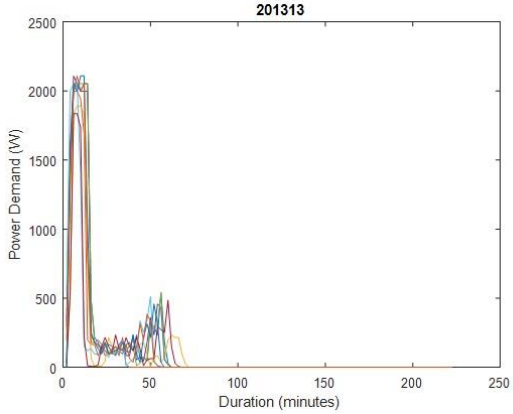

203109
Power Demand (W)
Duration (minutes)

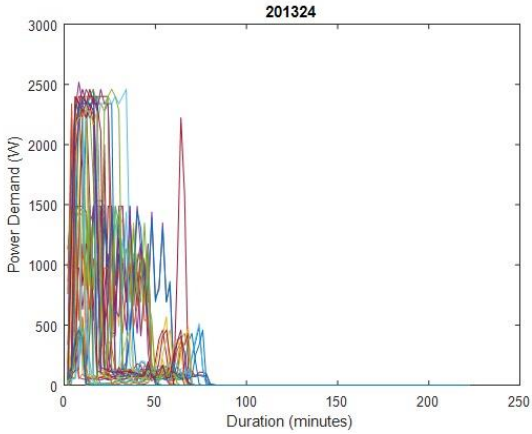

203195
Power Demand (W)
Duration (minutes)

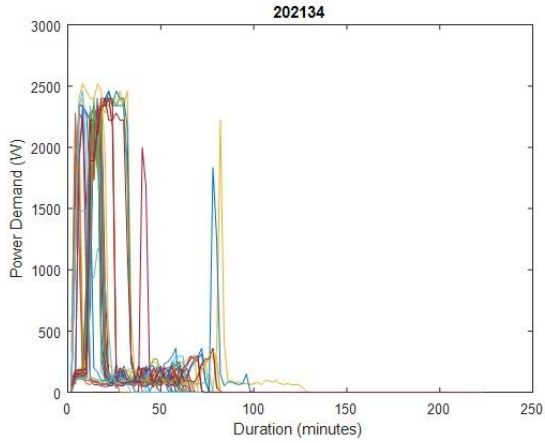

203200
Power Demand (W)
Duration (minutes)

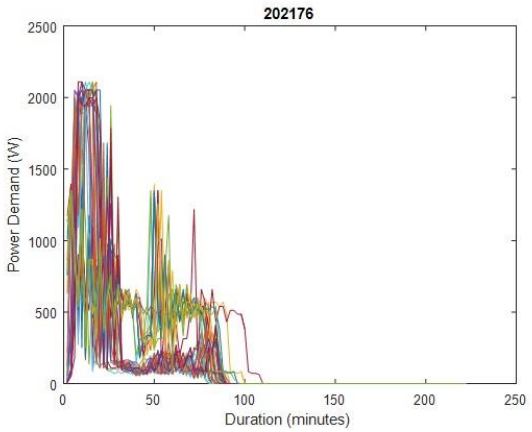
Washing-drying machines

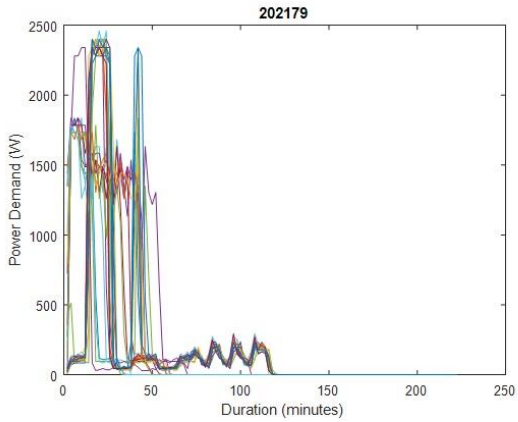


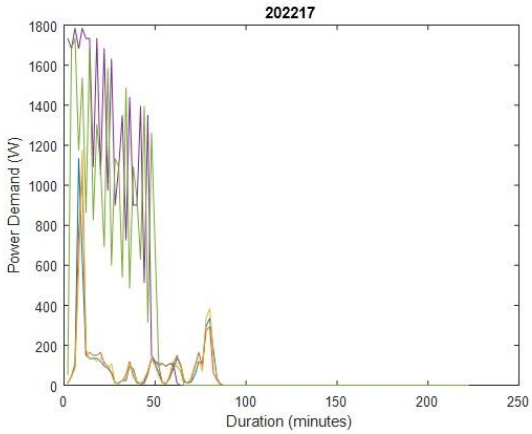


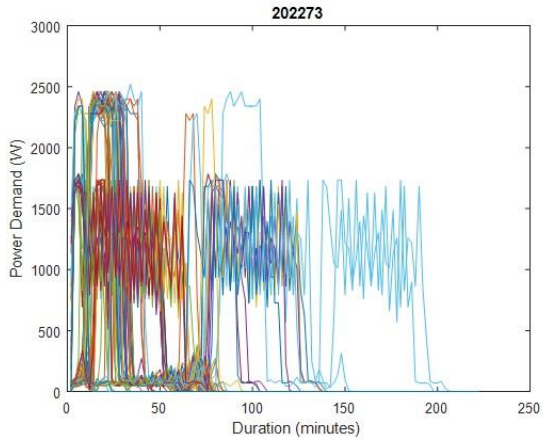


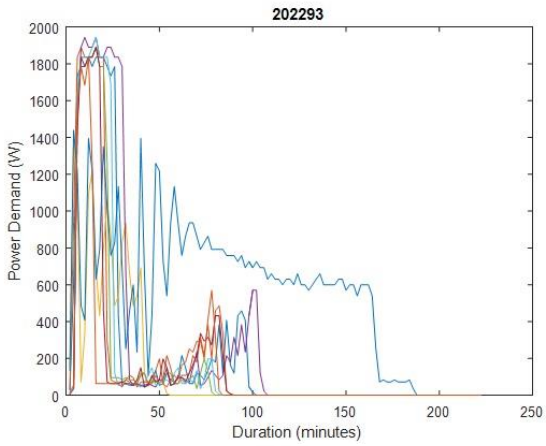


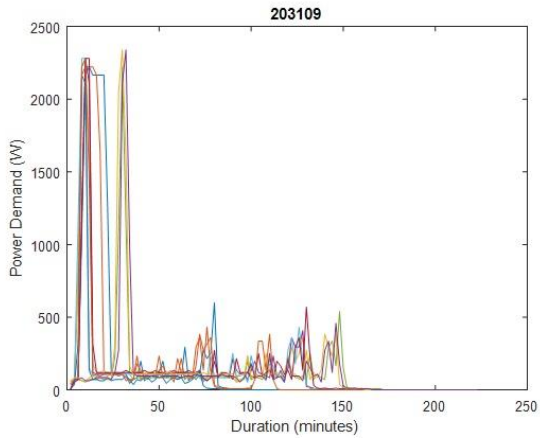


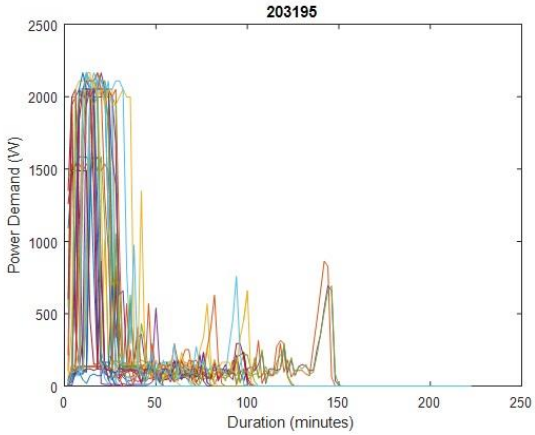


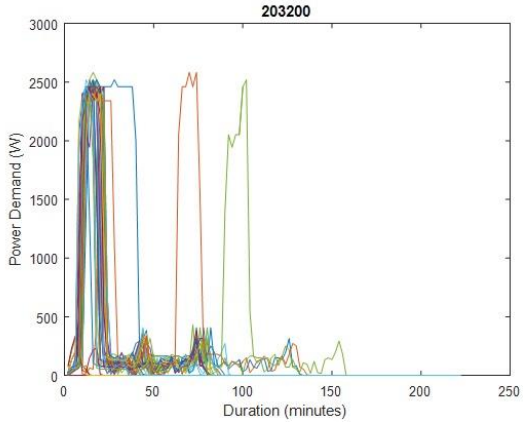




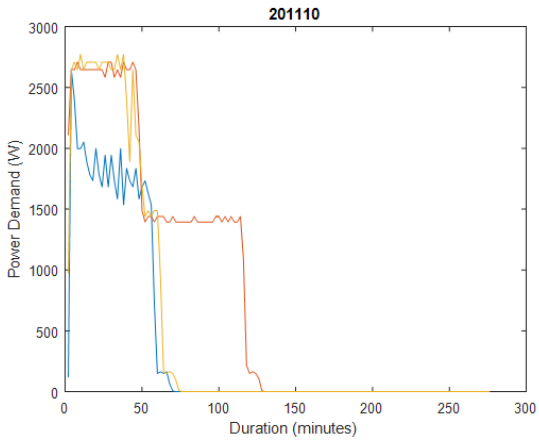


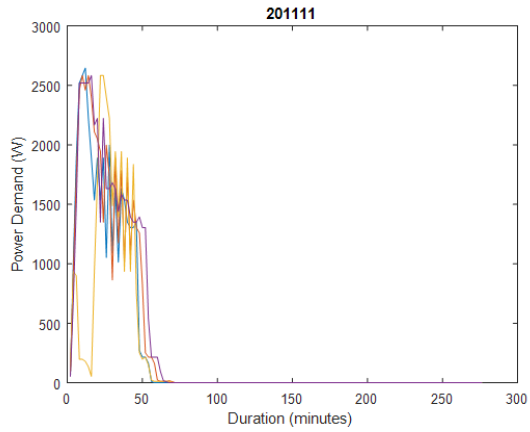


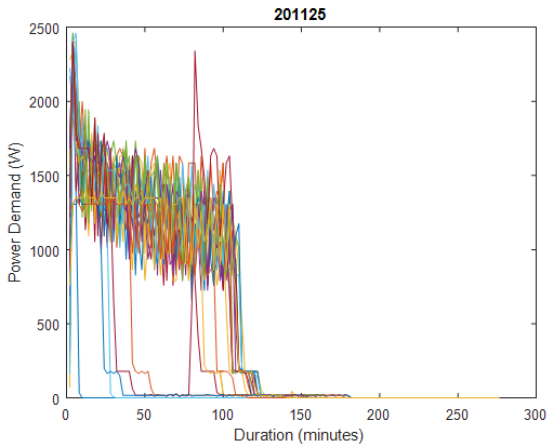


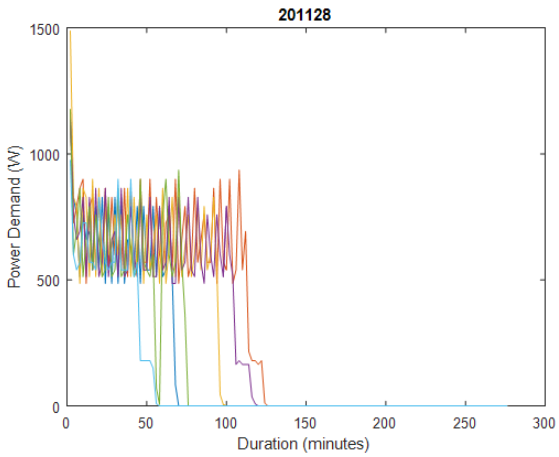


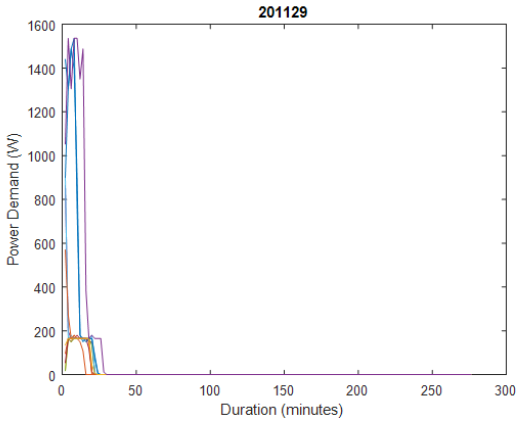
Tumble dryers

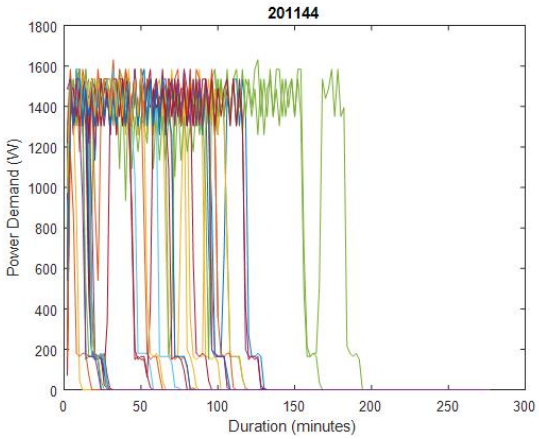


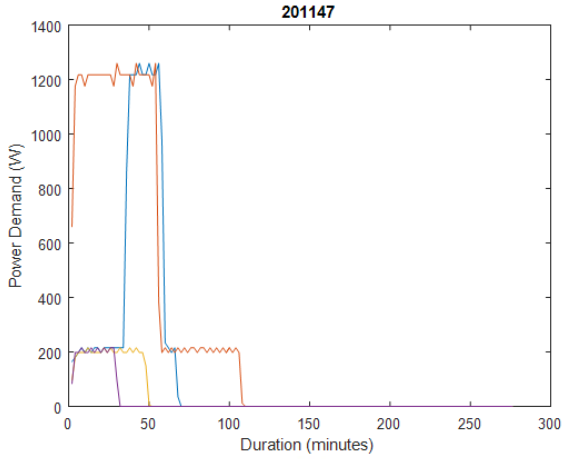


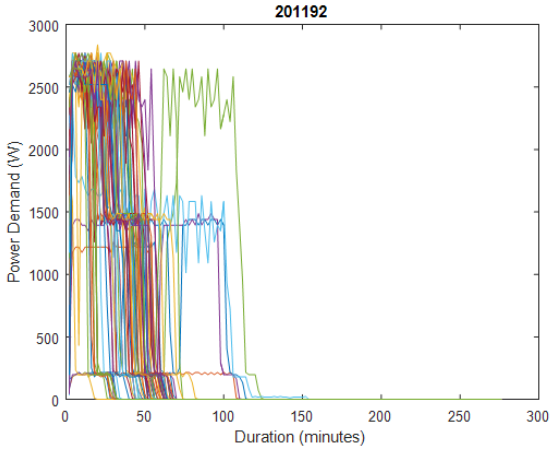

201125
Power Demand (W)
Duration (minutes)

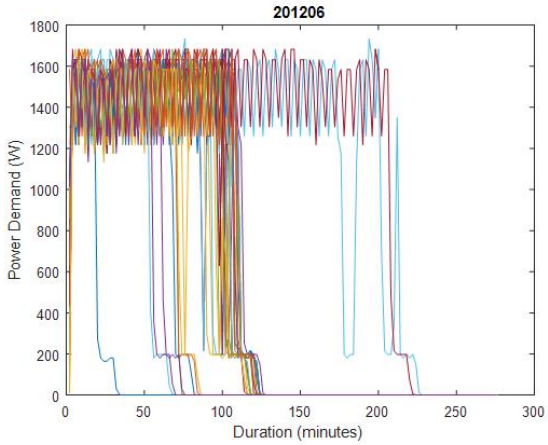

201128
Power Demand (W)
Duration (minutes)

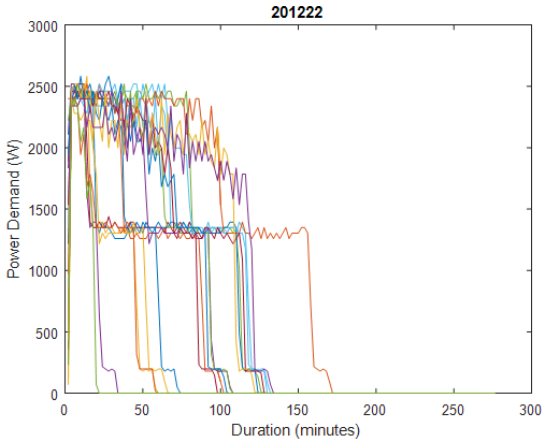

201129
Power Demand (W)
Duration (minutes)

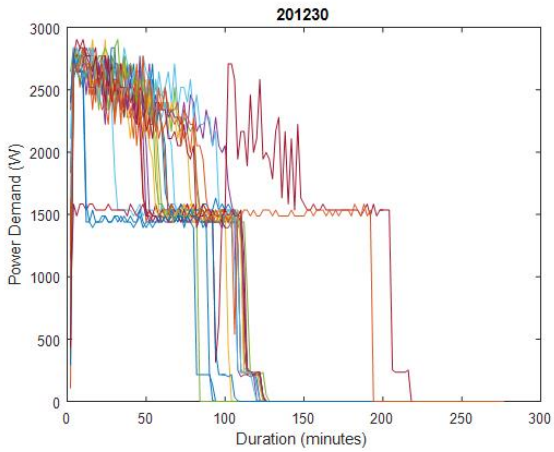

201144
Power Demand (W)
Duration (minutes)

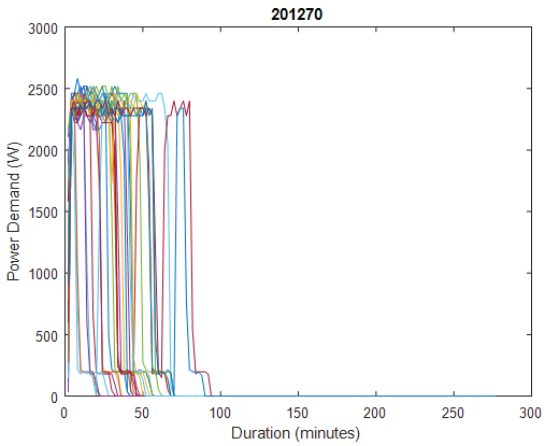

201147
Power Demand (W)
Duration (minutes)


201192
Power Demand (W)
Duration (minutes)

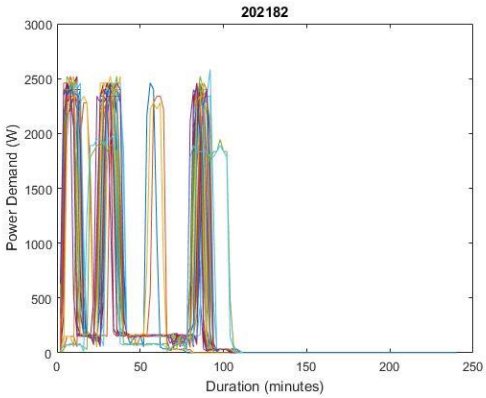

201206
Power Demand (W)
Duration (minutes)

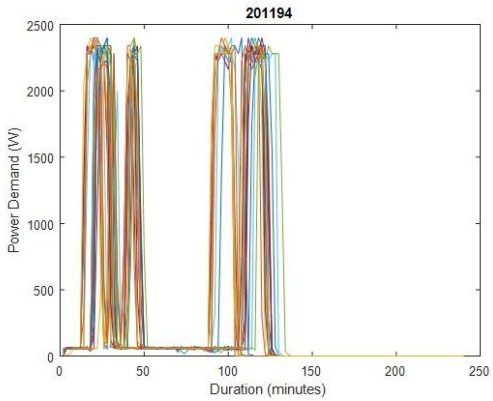

201222
Power Demand (W)
Duration (minutes)

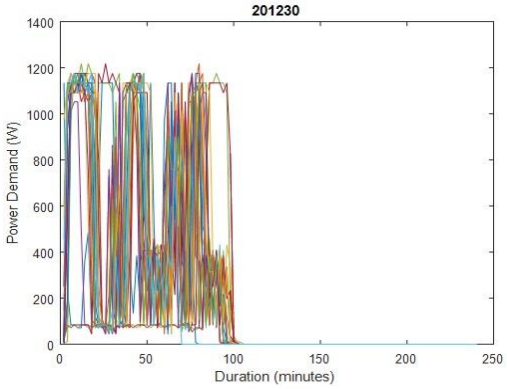


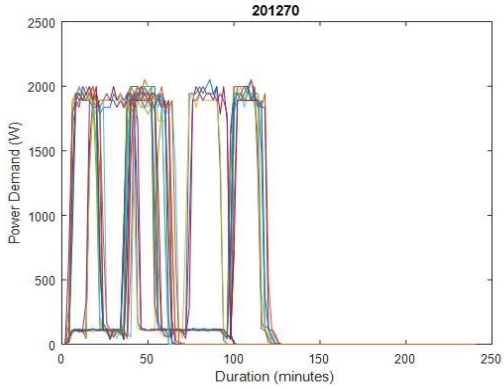


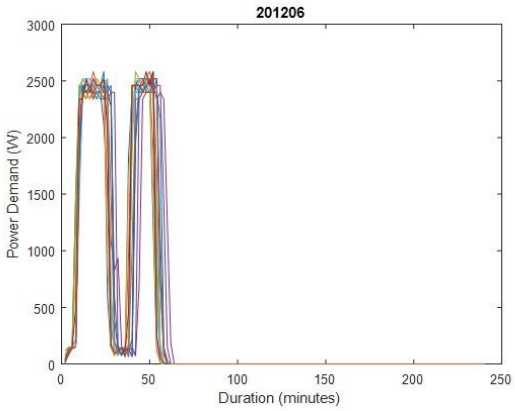
Dishwashers

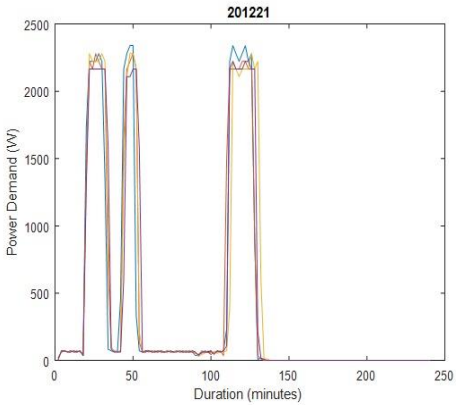


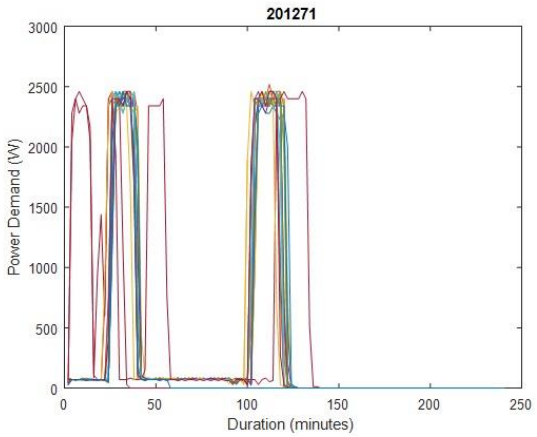


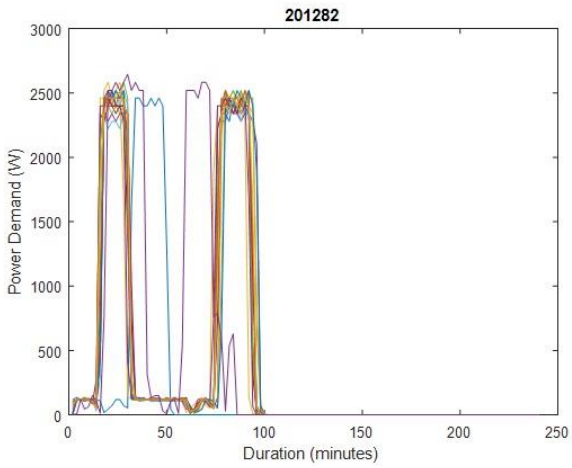


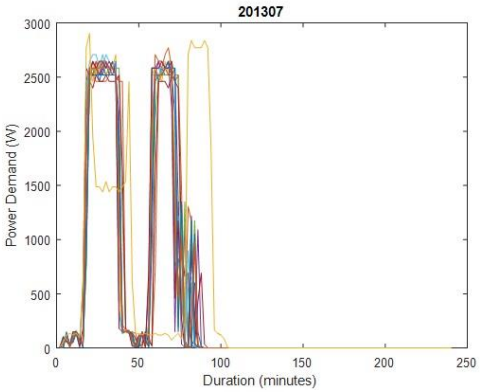


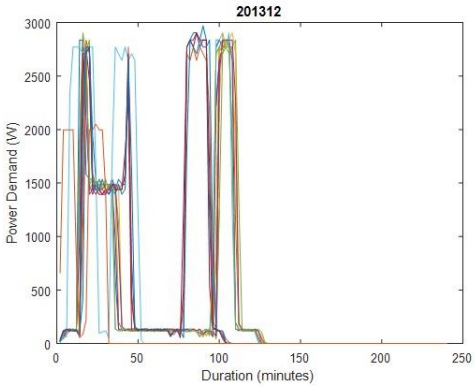


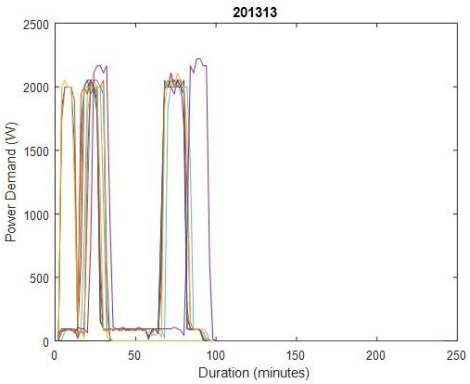


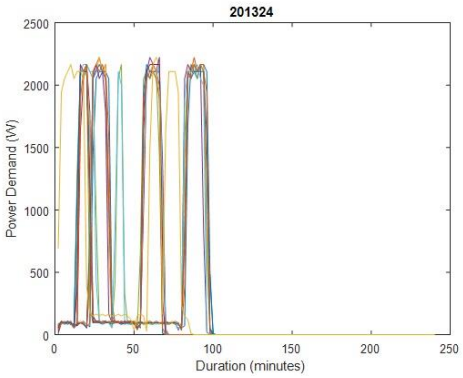

201271
Power Demand (W)
Duration (minutes)


201282
Power Demand (W)
Duration (minutes)

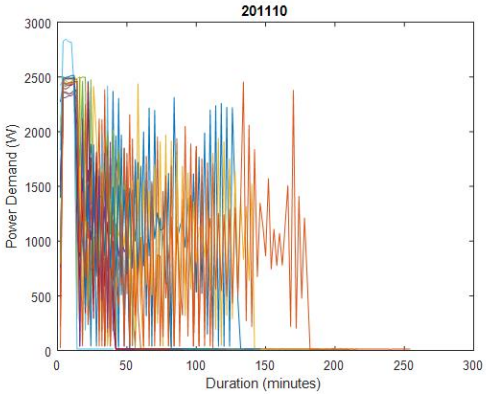

201307
Power Demand (W)
Duration (minutes)

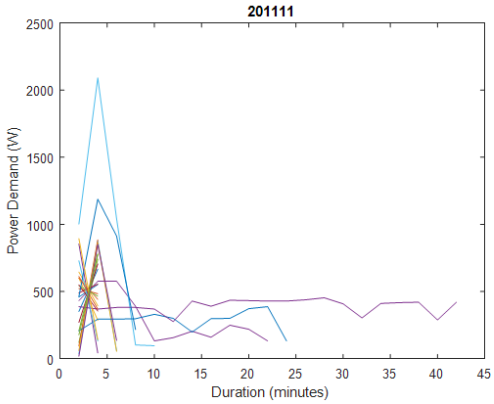

201312
Power Demand (W)
Duration (minutes)

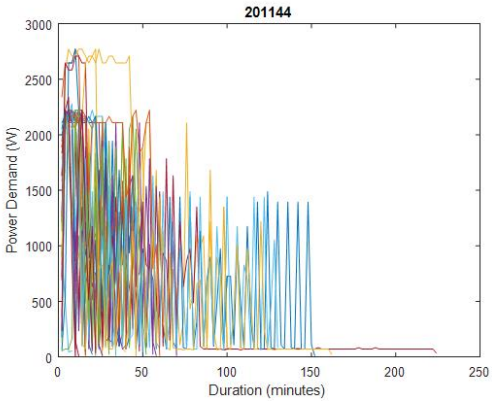

201313
Power Demand (W)
Duration (minutes)

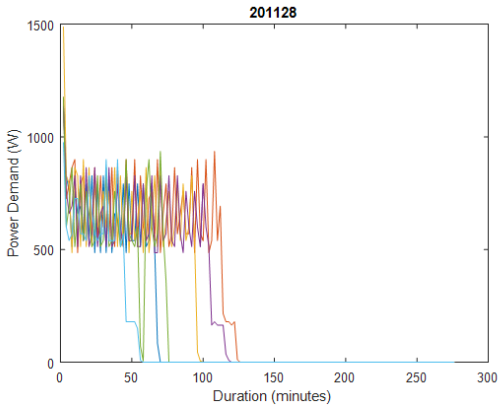

201324
Power Demand (W)
Duration (minutes)

Cookers

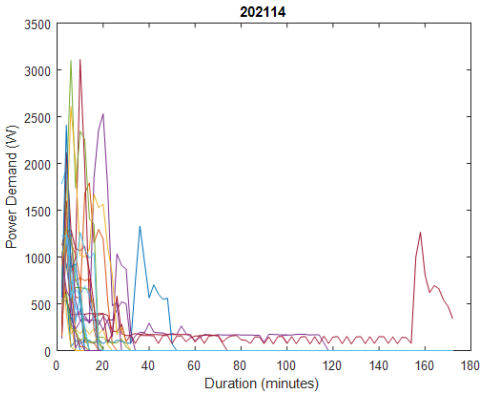

201110
Power Demand (W)
Duration (minutes)

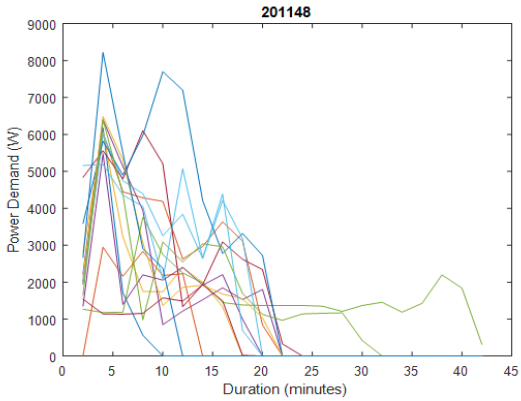

201111
Power Demand (W)
Duration (minutes)

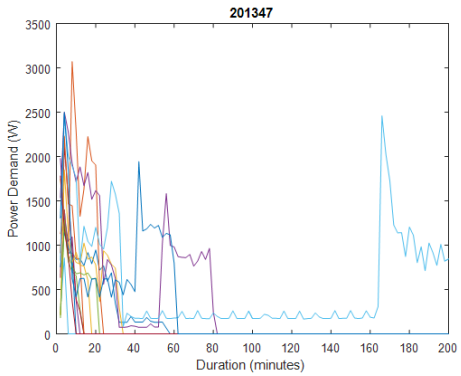

201144
Power Demand (W)
Duration (minutes)


201128
Power Demand (W)
Duration (minutes)

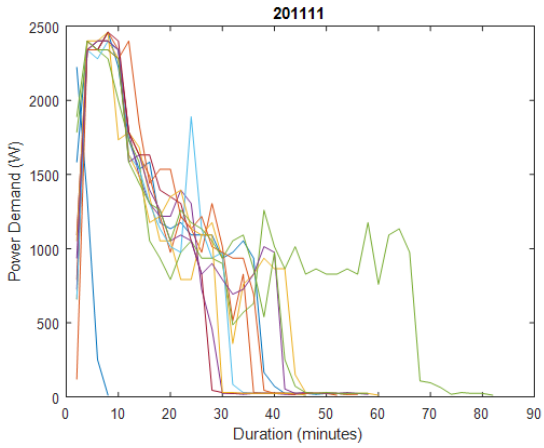
Hobs

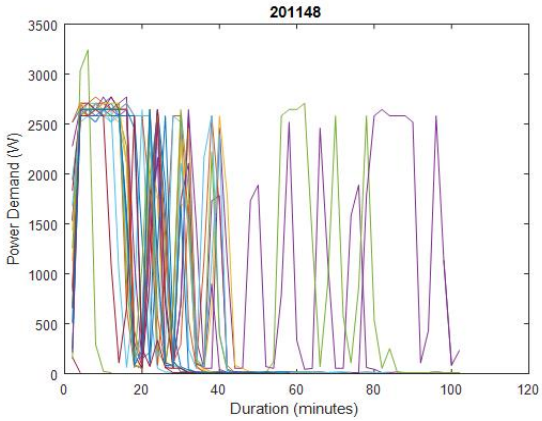

202114
Power Demand (W)
Duration (minutes)

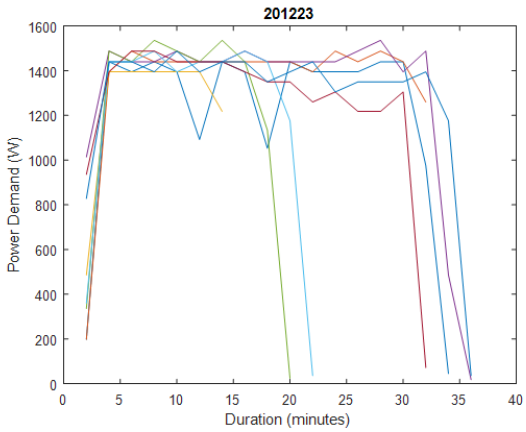

201148
Power Demand (W)
Duration (minutes)

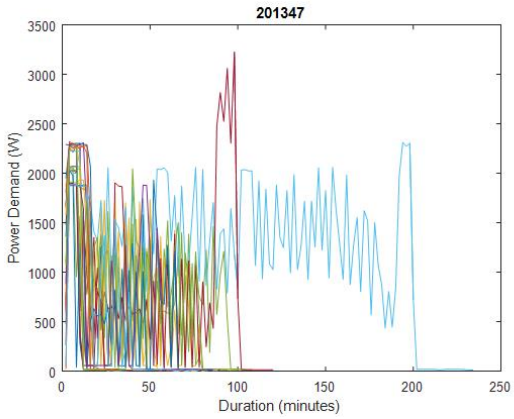

201347
Power Demand (W)
Duration (minutes)

Ovens

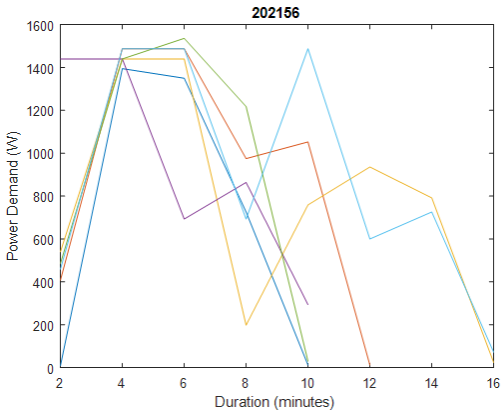

201111
Power Demand (W)
Duration (minutes)

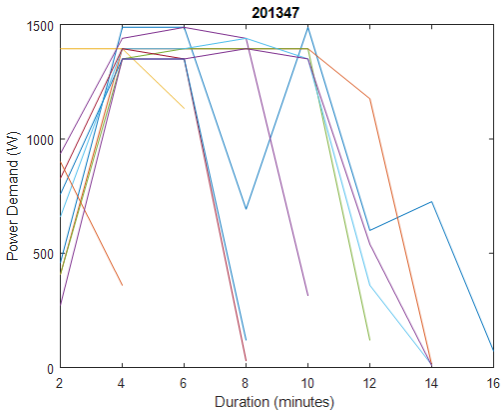

201148
Power Demand (W)
Duration (minutes)

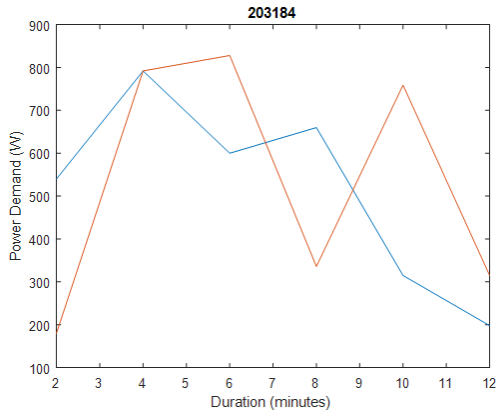

201223
Power Demand (W)
Duration (minutes)

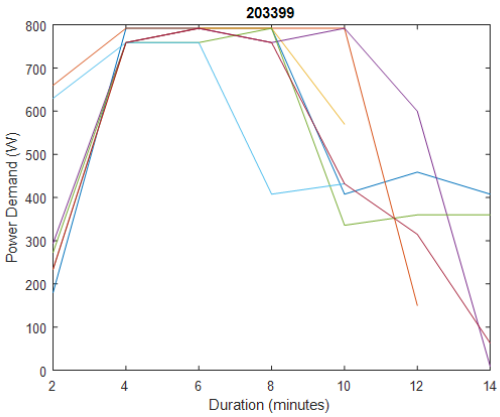

201347
Power Demand (W)
Duration (minutes)

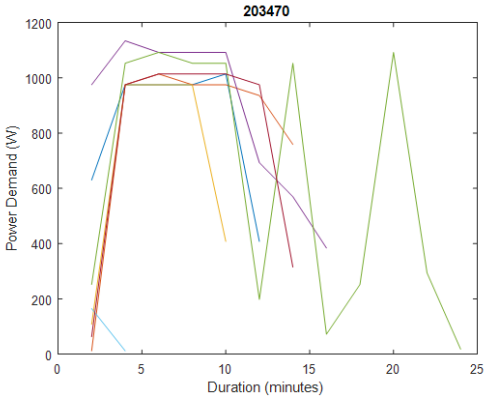
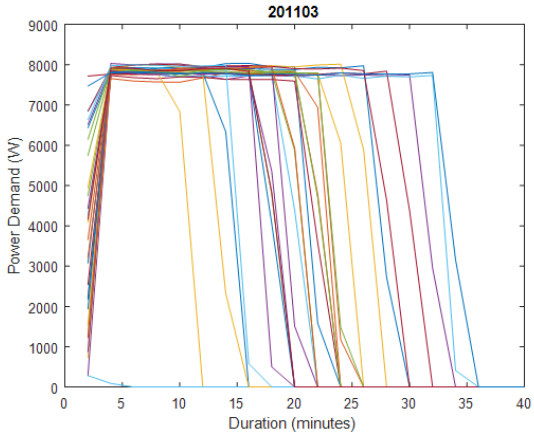
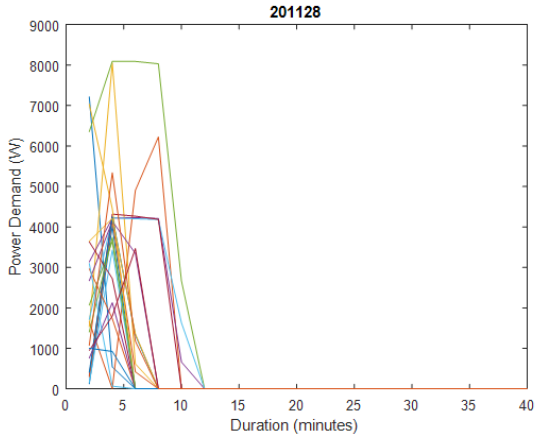
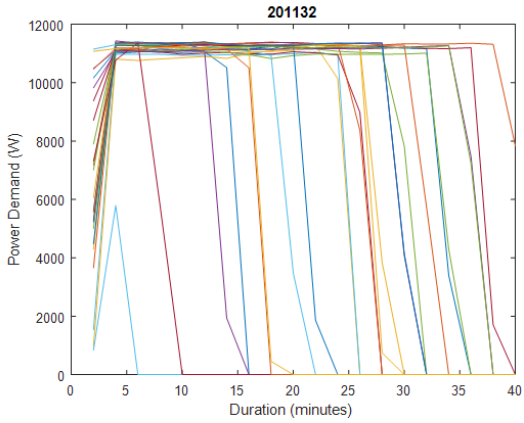
Grills


202156
Power Demand (W)
Duration (minutes)


201347
Power Demand (W)
Duration (minutes)


203184
Power Demand (W)
Duration (minutes)


203399
Power Demand (W)
Duration (minutes)


203470
Power Demand (W)
Duration (minutes)

Electric showers