The Socio-Economics and Energy Demand – United Kingdom Model (SEED-UK) Understanding the Dynamics, Diversity and Socio-Economics of the UK Domestic Stock

Trevor Sweetnam[1], Catalina Spataru[1], Mark Barrett[1]
[1]UCL Energy Institute, University College London,
14 Upper Woburn Place, London, WC1H ONN, UK

Abstract

Domestic energy demand is driven by the patterns of energy services required in the home as people go about their daily lives. Understanding these patterns, both how they combine with the physical determinants of energy demand, such as the building stock, and how they vary amongst our society is important when designing time of use tariffs and demand response programs.

This paper presents the Socio-Economics and Energy Demand – United Kingdom (SEED-UK) model, a dynamic model of the UK domestic stock. The model is built using a bottom-up framework combining both statistical and physics based techniques to create daily and seasonal electricity and heat demand profiles at a 10 minute time step as well as estimates of total consumption for a series of household types and sizes.

The model synthesis a number of previously developed models and approaches and capitalises on a number of large datasets describing the UK population and energy demand in the UK which have been summarised and linked in order to create probabilistic relationships for example between socio-economic groups, appliance sets and dwelling type, the 'technical environment'. The dynamics of energy services demand within this 'technical environment' are driven by a simulation of household activity which allows electricity, hot water and heating demand patterns to be simulated. Model performance is evaluated using a dataset which contains the gas and electricity demand profiles of 15,000 UK domestic customers.

This paper presents the resulting electricity and heat demand profiles which highlight subtle differences between the consumption patterns of socio-economic groups. Understanding and quantifying these differences and the diversity of demand between and within groups provides important data for the design of time of use tariffs and demand response programs.

1.0 Introduction

Domestic energy demand is driven by the patterns of energy services demand in the home and shaped by a diverse range of operational and technical aspects of appliances, building systems and building fabric.

Many previous studies have addressed dynamics, diversity and socio-economics of energy demand. As far as we are aware, the work described in this paper is the first to address all three of these important aspects and model both domestic electricity and heat demand in the UK context.

Demand for energy services is highly dynamic, depending on the actions and habits of the household, the resulting energy demand patterns are as diverse as the appliance and building stock creating significant complexity.

Diversity, in terms of the contribution of individual consumer load profiles to network peak load, is well understood in engineering terms however this understanding is somewhat superficial. By taking a bottom up approach the model described in this paper aims to better understand the behavioural and technical drivers of this diversity. This is particularly relevant where new demand response programs and the introduction of automation risk breaking the old assumptions about stochastic consumer behaviour.

Understanding and modelling the dynamics and diversity of domestic energy demand may therefore provide insights in a number of areas. The main area of interest that has motivated this work is the provision of domestic demand response. Here, diversity can be both a benefit and a barrier. Diverse patterns of demand can be extremely useful in creating demand flexibility. However, differences between households mean that pricing structures need to be carefully designed in order to avoid disadvantaging those who cannot afford to pay. This is an important topic for the energy industry, which has already suffered bad-press in recent years.

This paper describes a bottom-up model that uses a number of datasets that describe household activity, the UK building and appliance stock. It begins with a discussion of other work which has addressed dynamic modelling of energy demand and studies that have examined the variation in energy demand patterns among socio-economic groups. Finally, some model outputs are presented and discussed with a particular focus on their importance for the design of demand response programs.

2.0 Simulating Domestic Energy Demand

Analysing, understanding and modelling domestic energy demand is a field of study that has attracted significant interest among academics in building, physics and more recently social-science disciplines over the years resulting in a significant body of work.

The problems being addressed by this work range from understanding the consumption of the domestic stock and the potential for improvement to inform policy, creating synthetic electricity demand data for the design of networks, understanding the potential of dwellings to contribute to the operation of electricity networks and addressing the impact of occupant behaviour on energy demand.

The SEED-UK model has interests and potential applications in all of these areas however it's development has been driven by an interest in exploring the impact of new time of use tariffs and other demand response programs. Many of these have been field tested among small numbers of households however little is known about the impact they might have on the UK population as a whole.

In the UK, domestic energy policy has been influenced heavily by the work of Shorrock and others on the BREDEM (1991) what have been incorporated in the UK Government's (2012) Standard Assessment Procedure (SAP) models. These single dwelling models have formed the basis for many other analyses and modelling exercises such as the more recent endeavours Cambridge Architectural Research [CAR] on the UK Housing Energy Fact File (Palmer & Cooper, 2013) which draws on the English Housing Survey dataset (UK Government, 2015). Murphy, Khalid and Counsell (2011) and Baster (2011) have also built on this work, creating a version of the model that represents the dynamics of building physics while retaining the relatively small number of inputs.

A number of modelling frameworks have been published that attempt to use data on household activity to derive energy services demand profiles and understand the dynamics of energy demand. In particular, work by Richardson et al (2010) and Widén and Wäckelgård (2010) who have successfully used data describing individual's activities in the home to create electricity load profiles.

Network scale modelling, such as that carried out by Strbac (2012) and others have focused on the benefits of smarter electricity networks and make high level assumptions about the operational characteristics of demand shifting and energy storage. These studies have pointed to the potential for the domestic sector to contribute, through deployment of heat storage for example, but do not address the detailed operational performance which is dependent on underlying patterns of consumption, building fabric and building systems.

Hong et al (2015) point towards the huge influence that occupant behaviour has on the energy demand of buildings and develop a framework or ontology to allow behaviour to be incorporated in building simulation in a standardised way. Hong's work delves deeper into the interactions of occupants and building systems, an area that is likely to be of great importance to demand response schemes that rely on human interaction and may be relevant to future iterations of the model presented here.

Returning to the area of demand response programs and demand flexibility many field studies of various approaches have been carried out with trial populations of modest proportions (Sweetnam, Spataru, & Barrett, 2015). The success of these approaches and their impact on the population at large is difficult to predict although Sustainability First (Sustainability First, 2011)have done a detailed top down analysis using UK domestic demand profiles. The limitation of applying top-down modelling in this area is that the diversity of demand between and within different groups of society is not captured.

The SEED-UK model synthesises and extends many of the previous pieces of work mentioned in this section. The basic framework of an activity driven model is drawn from the work on Richardson and Widen in particular. The representation of the UK domestic stock synthesises the work of CAR and Murphy to create a dynamic stock model. New models to represent the dynamics of hot water demand and household space heating demand are added to this work. This enables us to present a comprehensive representation of the dynamics of UK domestic electricity and heat demand that is data driven and allows the diversity of demand to be explored.

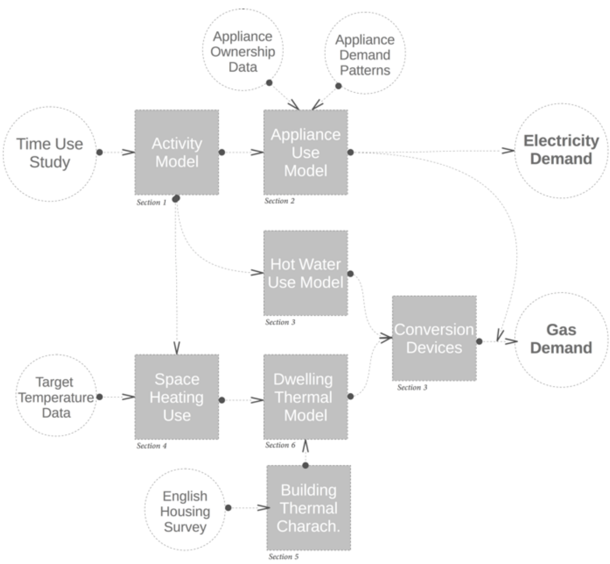

Figure 1: Model Overview

3.0 The SEED-UK Model

The SEED-UK model takes a bottom up approach that aims to capitalise on the available input data for the UK and better understand the diversity in domestic energy demand between socio-economic groups than more high-level top down approaches.

Occupant activity as described in the UK Time Use Survey (UK TUS) (UK Data Service, 2000) is the central driver within the model. The UK TUS data has a 10 minute resolution therefore this is adopted throughout the modelling.

Household activity forms a basic input to electricity and hot water and space heat demand models. These elements are described in turn in this section before model evaluation using UK domestic energy demand data is described.

3.1 Activity Model

Energy demand is fundamentally driven by the actions of end users; therefore, having resolved to take a bottom-up approach, household activity is the starting point of the modelling framework.

The UK TUS is a large dataset that documents the activities of the UK population. Many of the activities documented in the TUS can be used to deduce when the individual is at home and active (i.e. not asleep). Processing this data yields a time series that describes the proportion of homes that have active occupancy at any time, which is useful in generating heating schedules, for example. The activities themselves can further be used to deduce the use of certain appliances, hot water and so on. Table 1 links the detailed TUS activity codes to the 8 activities defined in the simplified diary data.

Simplified Activity	Code	Detailed Activity	TUS Range	
			Start	End
Asleep/Out	0	Arts	7000	7190
		Care Giving	3800	3919
		Classes	2110	2110
		Gardening	3400	3410
		Hobbies	7200	7390
		In Bed	10	120
		Pet Care	3420	3490
		Resting	5310	5310
		Shopping	3600	3690
		Socialising	5000	5299
		Sport	6000	6312
		Travel	9000	9890
		Volunteering	4000	4390
		Work	1000	1399
Personal Care	1	Personal Care	300	390
		Unspef. Personal Care	0	0
		Wash and Dress	310	310
Cooking/Eating	2	Eating	210	210
		Food Management	3100	3190
Cleaning	3	Cleaning	3200	3290
		DIY	3500	3590
		Household Care	3000	3000
Laundry	4	Laundry	3300	3390
ICT	5	Computing	7220	7330
		Internet	3710	3729
		Study	2000	2210
TV & AV	6	Music	8300	8320
		TV	8210	8229
Other	7	Other or None	9940	9990
		Reading	8000	8190

Table 1: Activity Categories

Alongside the activity diaries, the TUS dataset also contains information about the employment status and income of the individuals and households surveyed.

From this data we have defined four socio-economic groups as described in Table 2. The division is primarily concerned with employment status although we divide 'employed' households into a group facing 'adversity' and a group who are termed 'affluent'. 'Adversity' is defined as having a gross household annual income of less than £20,860. A value at the lower end of the range defined by the Joseph Roundtree Foundation (2016) which varies from £17,000 to £40,000.

Household Structure	Count	Group	Group #	%
Both Employed & Below Income Threshold	598	Employed Adversity	1	24.7%
1 Unemployed, 1 Employed Below Income Threshold	518			
1 Retired, 1 Employed Below Income Threshold	79			
Both Employed & Below Income Threshold	1006	Employed Affluent	2	39.6%
1 Unemployed, 1 Employed Above Income Threshold	797			
1 Retired, 1 Employed Above Income Threshold	113			
Both Unemployed	692	Unemployed	3	14.3%
1 Retired, 1 Unemployed	115			
Both Retired	917	Retired	4	21.3%
Total	**4835**			**100.0%**

Table 2: Socio-Economic Grouping

Having completed data cleaning and these two data processing steps the simplified diaries for each of the socio-economic groups are used to create a Transition Probability Matrix (TPM) which described the probability of being in each of the 8 states given the current state for each time step in a similar manner to that described by Widén and Wäckelgård (2010). A random walk algorithm using these TPMs is then used to generate activity profiles for each household member which are then combined to describe all ongoing activities in the home. Figure 1 is an example household profile.

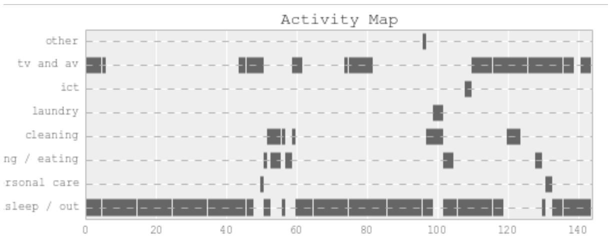

Figure 1: Example Activity Map

3.2 Electricity Demand Model

The electrical demand model links the household activities to their use of electricity consuming appliances. The model extends the approach taken by Richardson et al (2010) by utilising, appliance ownership data per socio-economic group, from the Energy Follow Up Survey (EFUS) (UK Data Service, 2011) to assign an appliance set to each household.

The model has three principle steps as illustrated in Figure 2:

- First, for a given household type an appliance set is assigned given the ownership probabilities set out in Table 3.
- Second, a series of simple appliance demand patterns are generated depending on whether the appliance has a Cyclic demand pattern,

occurs concurrently with the activity (Type A), begins operating during the activity and continues afterwards (Type B) or occurs concurrently and has a stand-by load (Type C). The presence of daylight is modelled for the creation of lighting demand.

- Third, the model steps through the household activity profile and activates the appliances linked to each activity when a randomly chosen number is less than the switch-on probabilities. Switch-on probabilities are varied in order to fit the model as described by Richardson.

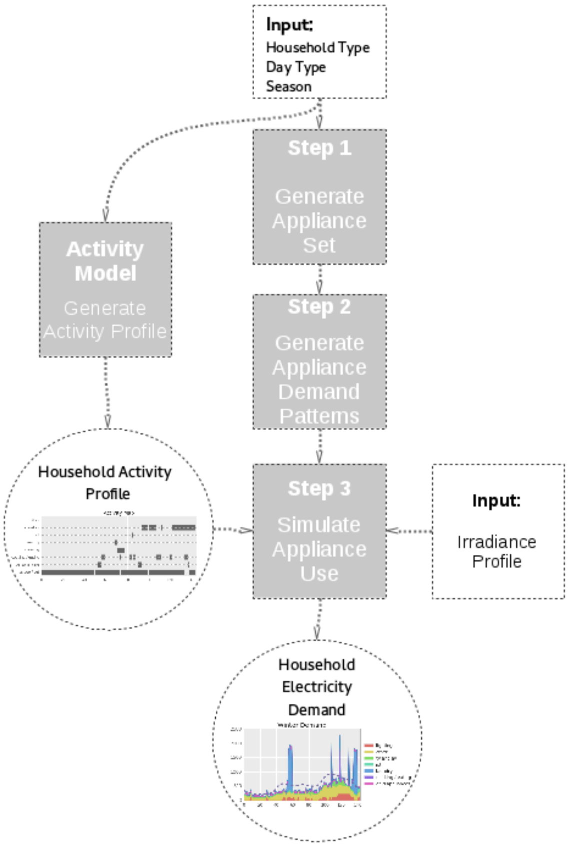

Figure 2: Electricity Demand Model

Appliance	Ownership Rate Group 1	Group 2	Group 3	Group 4	Source	Demand Category	Activity Code(s)
Refrigerator	99%	99%	99%	99%	EFUS	Cold Appliances	-
Freezer	93%	96%	91%	94%	EFUS		
Lighting	100%	100%	100%	100%	-	Lighting	1 – 7
Electric Shower	48%	48%	48%	48%	MTP	Showers	1
Hob	38%	38%	38%	38%	EFUS	Cooking	2
Oven	68%	68%	68%	68%	EFUS		
Microwave	82%	86%	81%	82%	EFUS		
Kettle	100%	100%	100%	100%	-		
Dish Washer	26%	49%	19%	38%	EFUS	Wet Appliances	3
Washing Machine	96%	99%	94%	95%	EFUS	Wet Appliances	4
Tumble Dryer	54%	68%	55%	60%	EFUS		
Computer	80%	90%	80%	80%	-	ICT	5
TV	220%	260%	210%	210%	EFUS	TV & AV	6
Stereo	80%	80%	80%	80%	ONS		

Table 3: Appliance Ownership Probabilities

Appliance	Demand Pattern	Switch-On-Probability
Refrigerator	Cyclic	-
Freezer	Cyclic	-
Lighting	Daylight-Dependent	-
Electric Shower	Type A	0.05
Hob	Type A	0.025
Oven		0.02
Microwave		0.03
Kettle		0.025
Dish Washer	Type B	0.2
Washing Machine	Type B	0.2
Tumble Dryer		0.05
Computer	Type C	0.9
TV	Type C	0.8
Stereo		0.4

Table 4: Appliance Switch on Probabilities

The appliances modelled account for approximately 75% of household demand when switch-on probabilities are calibrated to match the HEF data (see Figure 3). Therefore, a seasonally varying 'other/unknown' demand profile is added to the demand as a final step.

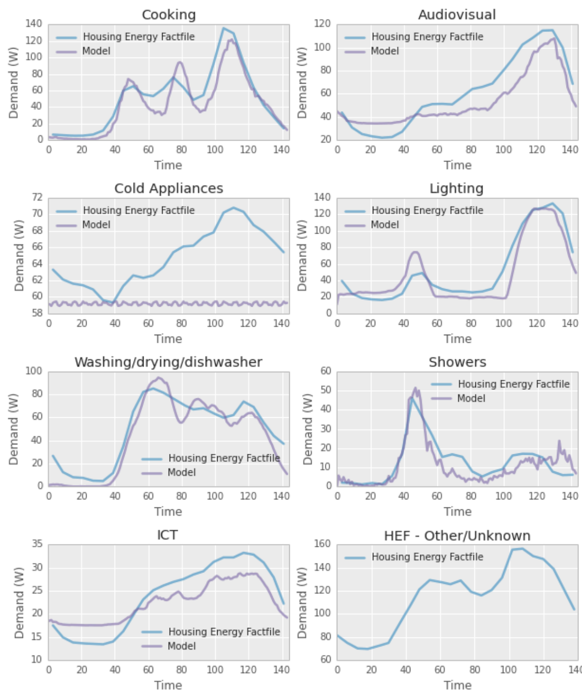

Figure 3: Model Generated & HEF Appliance Profiles

3.3 Heat Demand Model

One of the principle extensions of this framework beyond the work of Richardson and Widen is to address hot water and space heat demand. Modelling heat demand is complex as variation in building systems and building fabric have an important role in determining final demand. This section begins by describing the hot water demand model before moving on to describe the space heating and building fabric model.

Hot Water Demand

The hot water demand model proceeds in the same manner as the electricity demand model. Firstly, hot water consuming 'appliances' are assigned. In the case of hot water very little empirical data is available to determine ownership rates and consumption therefore values are assumed based on best available information, for example if 96% of Group 1 have a washing machine according to the EFUS, we assume 4% use the kitchen sink for dish washing.

Hot water demand profiles are deterministic. In this second stage the model steps through the household activity profile and triggers hot water use using the switch on probabilities, as described in Table 5. The resulting output profiles are in litres, which can be converted to energy demand in further steps depending on the building systems.

Appliance	Ownership Rate Group 1	Group 2	Group 3	Group 4	Source	Demand Category	Activity Code
Shower	1	1	1	1	N/A	Personal Care	1
Bath	1	1	1	1	N/A		
Basin	1	1	1	1	N/A		
Sink - Cooking	1	1	1	1	N/A	Cooking	2
Sink - Cleaning	0.74	0.51	0.81	0.62	EFUS	Cleaning	3
Sink - Laundry	0.04	0.01	0.06	0.05	EFUS	Laundry	4

Appliance	Switch On Probability	Consumption Rate (l/10m)	Time	Mean Daily Demand (l)
Shower	0.1	60	10	46.6
Bath	0.075	40	20	40.2
Basin	0.35	5	10	15.4
Sink - Cooking	0.05	20	10	
Sink - Cleaning	0.025	20	10	26.8
Sink - Laundry	0.05	20	10	

Table 5: Hot Water Consumption – Input Data

The Energy Saving Trust [REF] have measured hot water consumption in a small sample of 120 homes and produced hot water demand profiles. This is used to calibrate the switch on probabilities.

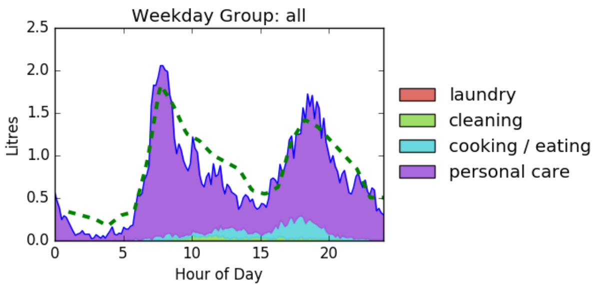

Figure 4: Model Generated & EST Hot Water Demand

Space Heat Demand

There is added complexity in modelling space heat demand due to the interaction of energy services demand, building fabric and building systems. This section deals with space heat demand starting with the determination of heating demand patterns before moving on to address the influence of the building fabric.

Heating Demand Patterns

Again, the starting point in determining heating demand patterns, or more precisely the comfort conditions demanded by household occupants, is their presence in the home and their desired temperatures.

PassivSystems (a UK home energy management system provider), have the heating schedules of 900 of their customers (Jin, 2012). This analysis has revealed a mean target temperature of 20.2°C (Std Dev 1.2°C), and a mean of 3.46 (Std Dev 0.71) state changes (i.e. from on to off & visa versa). In the absence of more representative data, target temperatures are drawn from a normal distribution with this mean and standard deviation.

Active occupancy can easily be deduced from the activity profile however on transforming this data into a heating schedule it is apparent that the number of state changes is far in excess of PassivSystems' findings. Therefore, an algorithm is applied to the schedule to remove short 'on' or 'off' periods, this reflects some 'inertia' in how the population controls their heating systems.

Building Fabric

The English House Condition Survey (EHS) (UK Government, 2015) is a large scale survey of the UK housing stock carried out periodically. The dataset is extensive and has been used in various modelling projects including the Cambridge Housing Model (CHM) (Cambridge Architectural Research, 2015).

Sufficient socio-economic data is available to relate the surveyed households to our four socio-economic groups and to characterise the UK stock within four dwelling types, flats (apartments), terraced houses, semi-detached houses and detached houses. Figure 5 and Figure 6 illustrate the results of this analysis which are intuitive, lower income, smaller families are more likely to live in apartments for example. The probabilistic relationships between socio-economic group and house types are used to assign households to dwellings.

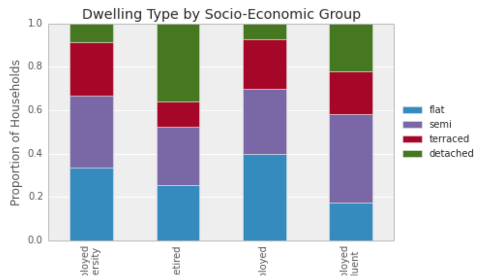

Figure 5: Socio-Economic Group & Dwelling Type

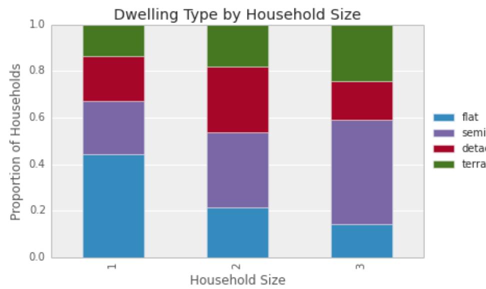

Figure 6: Household Size & Dwelling Type

Using a SAP-derived approach similar to the CHM each record in the survey is processed to determine the total floor area (TFA), heat loss coefficient (W/K) and thermal capacities (Wh/K) as required for the building physics model illustrated in Figure 7. Linear relationships between the TFA and these values are then derived for each of the four dwelling types.

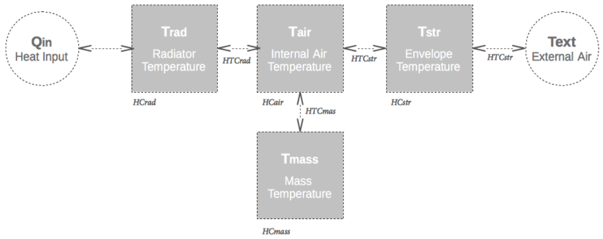

Figure 7: Dwelling Physics Model

The building physics model is similar to that presented in Sweetnam, Spataru and Barrett (2014) and is used alongside a simple control algorithm to calculate the heat input required to meet the household's comfort requirements taking the dynamics of the home into account.

The thermal model is flexible to be combined with a number of heat source depending on the scenario being simulated. For the purposes of model evaluation and this paper a gas boiler with a heating efficiency of 85% and a hot water efficiency of 65% (including pipework losses and so on), and a controller with a hysteresis band of 0.5°C is assumed.

Overview

In summary, for a given household group and size a space heating demand simulation proceeds as follows;

1. A target temperature is drawn from the distribution.
2. A heating schedule is determined by simplifying the active occupancy schedule.
3. A dwelling type is assigned using probabilities relating to the particular socio-economic group.
4. The dwelling TFA and thermal properties are assigned according to the dwelling type.
5. A building physics simulation is run to determine the heat input required to meet the household's target temperatures.
6. Heat input is converted to final energy consumption depending the heat source.

3.4 Model Evaluation

The UK Energy Demand Research Project (EDRP) (Ofgem, 2010) was a large study that gathered half hourly electricity and gas demand data from approximately 15,000 homes. The dataset contains basic geographic and socio-economic data for each of the households in the form of ACORN groupings (see: acorn.caci.co.uk) which can be related to our four socio-economic groups. The dataset is cleaned and processed to produce the demand distributions and profiles presented below. The geographic data is used along with historic UK weather data to create input external temperature profiles.

In order to evaluate the model performance and prepare the demand profiles presented in this paper a single model run representing 5,000 households has been conducted. The socio-economic groupings and dwelling types are per the input data.

Figure 8: Gas & Electricity Demand Distributions

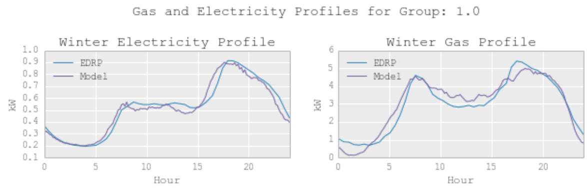

Figure 9: Group 1: Electricity & Gas Profiles

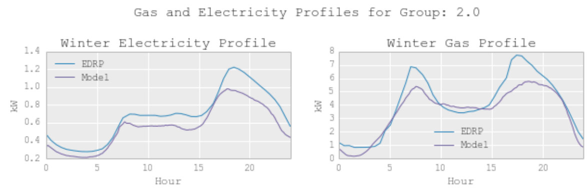

Figure 10: Group 2: Electricity & Gas Profiles

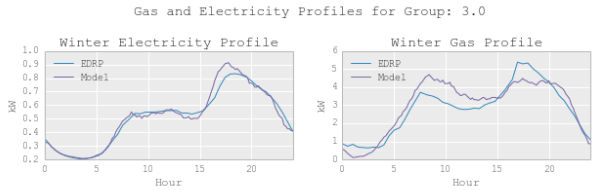

Figure 11: Group 3: Electricity & Gas Profiles

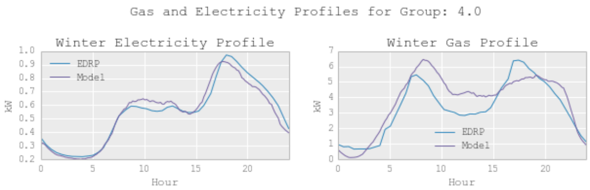

Figure 12: Group 4: Electricity and Gas Profiles

The model is evaluated in terms of total daily gas and electricity consumption for each of the seasons as well as weekday and weekend diurnal profiles. Only a selection are presented here for brevity, findings for the shoulder and summer season profiles are similar to those winter profiles presented above.

The evaluation results are relatively promising, in terms of electricity demand the modelled data has a slightly more compact distribution than the EDRP dataset, likewise the gas demand distribution however the agreement is acceptable. In terms of the electricity demand profiles agreement is excellent except for Group 2 (Employed Affluent) where demand is underestimated. The gas demand profiles show more varied results particularly in terms of the scale of the morning and afternoon peaks, however, overall there is relatively good agreement.

4.0 Results & Discussion

The SEED-UK model is capable of producing a multitude of demand profiles for the four socio-economic groups over a range of household sizes for weekdays and weekends in winter, summer and shoulder seasons.

There is little value in presenting all of these outputs, therefore, for the purposes of this discussion we will focus on the differences in demand patterns between the socio-economic groups, an area where the model has particular potential to deliver useful insight, and present only winter weekday demand profiles for the four groups. Our aim throughout this discussion is to explore the drivers and nature of the differences between the socio-economic groups.

4.1 Activity Patterns

Household activity is the starting point of the model. Figures 13 to 16 present the weekday activity profiles for each of the socio-economic groups. Already, differences are apparent between the lifestyles of our groups. Intuitively our unemployed and retired groups are more active during the day while our employed groups have more defined peaks.

This may have important implications for time of use tariff design. Could for example those groups that are home more often during the day provide more flexibility than employed groups? Would those who are in employment be unfairly penalised by high peak tariffs? Perhaps this is a desirable outcome as these groups are most able to pay.

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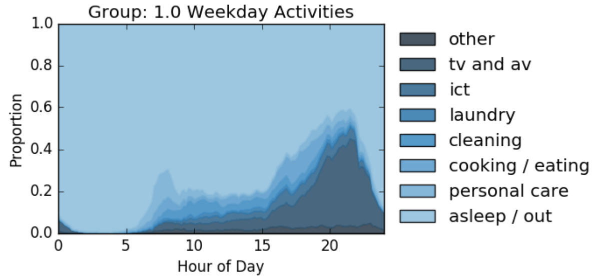

Figure 13: Group 1 (Employed Adversity): Weekday Activities

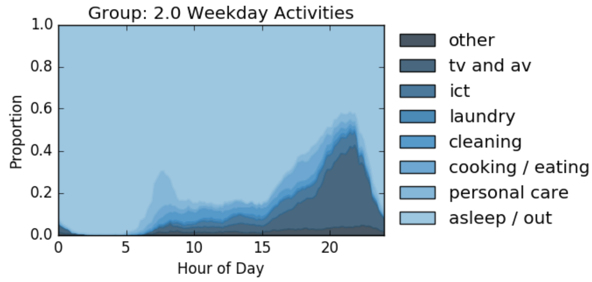

Figure 14: Group 2 (Employed Affluent): Weekday Activities

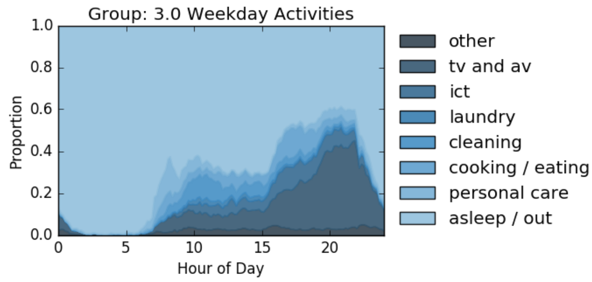

Figure 15: Group 3 (Unemployed): Weekday Activities

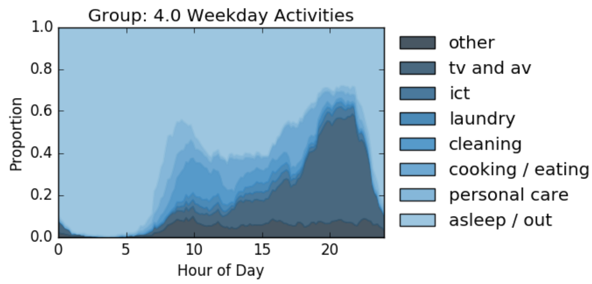

Figure 16: Group 4 (Retired): Weekday Activities

4.2 Electricity Demand

The electricity demand model layers differing appliance ownership rates among the socio-economic groups on top of the differing activity profiles. Here the differences become more subtle, due in part to the high proportion of unexplained, ‘other’, demand present in the winter profiles, but still apparent.

Our employed affluent group (Group 2) has notably higher peak and overall demand than the adversity group. Meanwhile, the retried group displays quite a striking difference in terms of demand during the late morning and middle of the day.

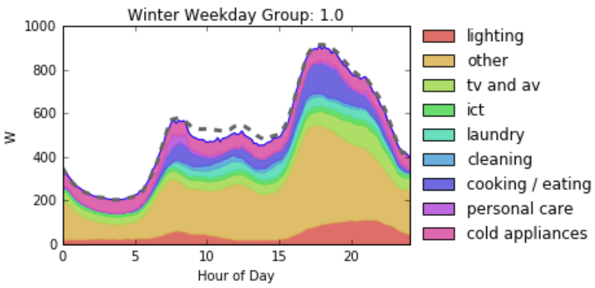

Figure 17: Group 1: Winter Weekday Electricity Demand

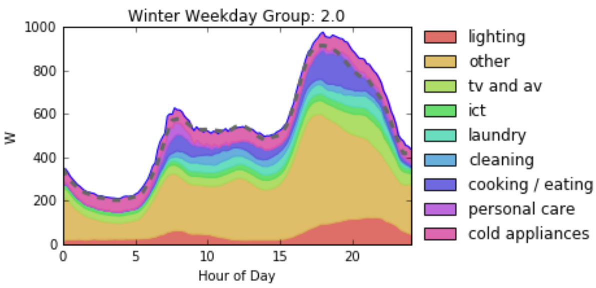

Figure 18: Group 2: Winter Weekday Electricity Demand

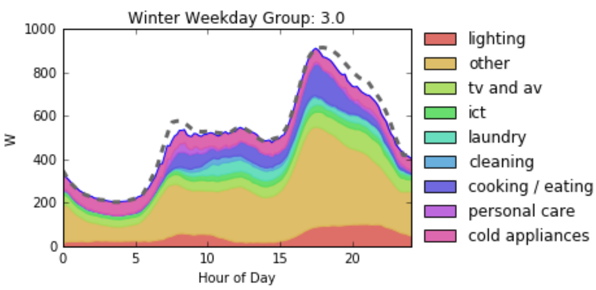

Figure 19: Group 3: Winter Weekday Electricity Demand

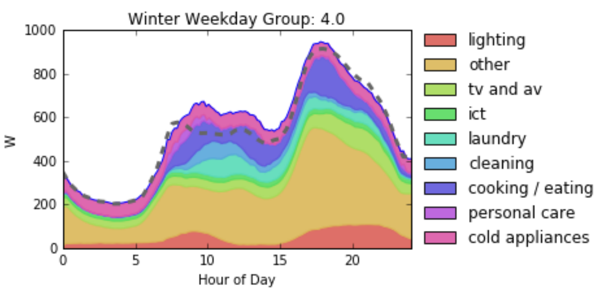

Figure 20: Group 4: Winter Weekday Electricity Demand

4.2 Heat Demand

The heat demand model includes both hot water and space heating demand. The hot water model is structured in a similar manner to the electricity demand model therefore, again, the outcomes are influenced by activity and appliance ownership rates. The heating model meanwhile, is influenced both by activity and statistics determining dwelling typology and building physics.

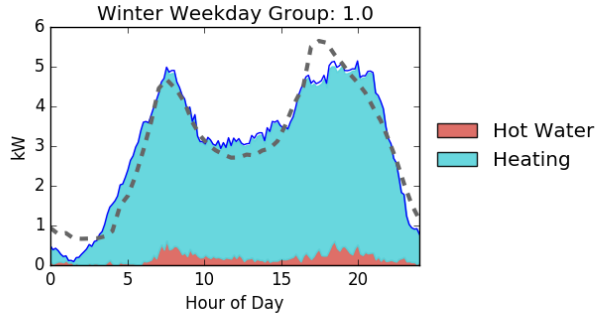

Figure 21: Group 1: Winter Weekday Heat Demand

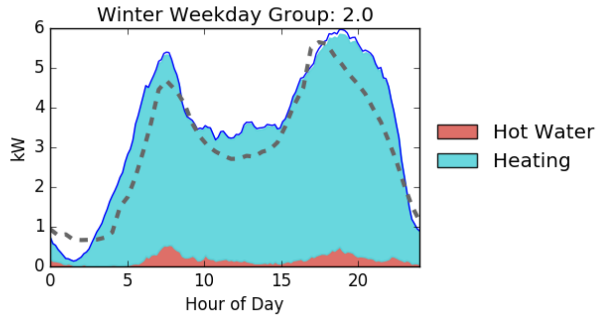

Figure 22: Group 2: Winter Weekday Heat Demand

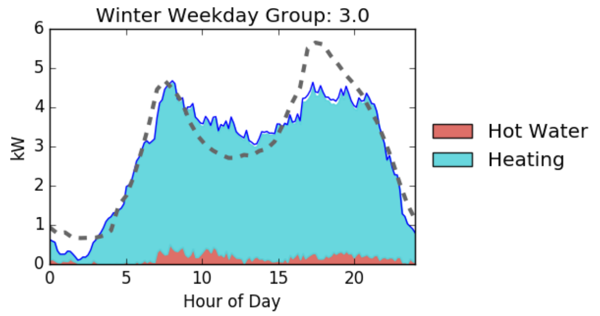

Figure 23: Group 3: Winter Weekday Heat Demand

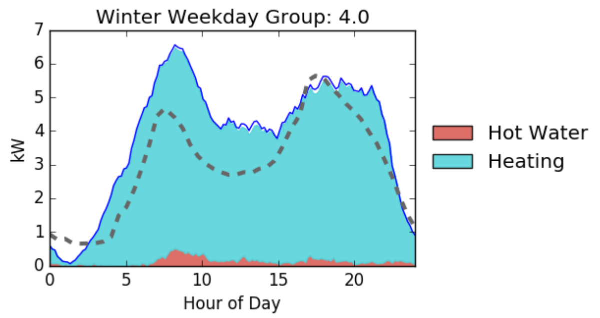

Figure 24: Group 4: Winter Weekday Heat Demand

Note: dashed lines indicated mean winter gas demand derived from the EDRP dataset.

The model results are perhaps more subtle than one might expect. Of our two 'employed' groups the 'affluent' Group 2, intuitively exhibits higher heating demand. As patterns of activity are similar and no differentiation is made on the assumed target temperatures this is likely driven by the greater tendency of this group to occupy detached and semi-detached dwellings.

The result for Group 4, the 'retired' group, is intuitive and also highlights an important issue of heat focused demand response schemes. For example, there is likely to be far less opportunity to time shift heat pump demand in these homes as heat demand is often near-constant throughout the day.

5.0 Conclusions & Further Work

This paper has presented a comprehensive, dynamic, model of UK domestic demand that syntheses a number of previous models and analyses in this area. The result is a comprehensive data-driven model that represents the dynamics and diversity of electricity and heat demand within and between a range of socio-economic groups.

The model has been evaluated using a top down method, facilitated by both UK national statistics and a dataset gathered within the Energy Demand Research Project.

In discussing a selection of the model outputs, this paper has aimed both to shed light on the importance of activities as an underlying driver of energy services and final energy demand, and demonstrate the potential of the modelling framework that has been developed.

By providing data that describes the subtle differences between the demand patterns of disparate groups within society and the diversity of demand patterns the model outputs will allow the impact of various demand response programs to be evaluated.

Although comprehensive, there are a number of limitations and weaknesses that should be pointed out. Many of these are the subject of ongoing work.

The TUS dataset is from a survey conducted in 2000 and therefore is quite old, a case for a new survey is being made. Patterns of activity may have changed. In addition, it does not provide sufficient data to allow differing activity profiles to be generated for each season. This is partly addressed through the calibration steps and the incorporation of seasonality in input temperature and daylight data. However, a deeper understanding of seasonality in activity would provide useful insights for tariff design around winter peak demand or summer peak renewable generation for example.

There are a number of areas where extensive data is not available and simplified assumptions have been made. Notably a single heating target temperature distribution is applied across all socio-economic groups. It may be expected that less affluent households have lower comfort expectations while retired, older, individuals have higher comfort requirements. Without further data to guide assumptions it is impossible to improve on the the current strategy.

In applying the model to the UK the authors have been fortunate to have access to a number of large-scale datasets describing domestic demand and activity. While few countries are likely to have such a breadth of input data available however the general framework of the approach is such, that as long as some data is available or assumptions can be made useful results may still be forthcoming.

The particular focus of this iteration of the model is diversity between socio-economic groups however the input data affords the opportunity to explore other parameters. Other possible applications are in incorporating more sophisticated representations of occupant action within the framework set out by Hong et al (2015), assessing the impact of building upgrade schemes on peak demand or changing lifestyles and household shapes on patterns of heat demand.

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