SAVE (Solent Achieving Value from Efficiency)

Report 2.1 – SAVE Customer Model Framework Specification

Document Ownership

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SAVE SDRC 2.1: SAVE Customer Model Framework Specification

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Contents

1 Introduction

The ‘Solent Achieving Value from Efficiency’ (SAVE) project aims to test the efficacy of a series of domestic electricity demand reduction interventions and to use the resulting data as the basis for the development of an evidence-based Network Investment Tool (Figure 1).

The interventions to be tested through a large sample domestic customer (household) trial will be:

1. Personalized data-driven messaging
2. Time-of-use incentives
3. LED light bulb replacement

These three intervention groups will be compared to a control sample and a randomised control trial approach will be implemented to ensure robust conclusions can be drawn. Data to be collected will include repeated social surveys, time use diaries and electricity consumption through half hourly (or finer) dwelling level monitoring and, for 50% of the households, smart plug monitoring.

In addition a community coaching trial (4) will take place in two areas of the Solent region alongside two matched control areas of similar neighbourhoods where no coaching will take place. Substation level monitoring of electricity demand in these areas will allow the effects of the interventions to be assessed, exploring in particular the relative effects of individual customers acting collaboratively, of collective community / stakeholder action and the subsequent sustainability of any behaviour change.

As Figure 1 shows, a major part of the foundation for the Network Investment Tool will be the SAVE Customer Model which has the following key objectives:

1. to capture and represent the data and insights from the three large sample trial groups and the control together with insights into the community or neighbourhood level effects of the community interventions;
2. to enable in-depth analysis of baseline and initial intervention trials to support iterative intervention design;
3. to support the analysis the effects of the household level interventions and the development of household level demand response scenarios under a range of conditions incorporating, where feasible, insights from the community coaching trial;
4. to produce baseline, intervention and scenario-based outputs as input to the Network Modelling Tool;
5. to support the production of baseline, intervention and scenario-based local area demand profiles

The SCMF will be developed in three phases:

1. Model Creation and Specification (Delivery: December 2014)
2. Baseline Model: (Delivery: December 2016) – to include initial waves of data collection and pre-trial baseline;
3. Final model: (Delivery: June 2018) – to include subsequent waves of data collection, post-trial results and a web-based dissemination tool.

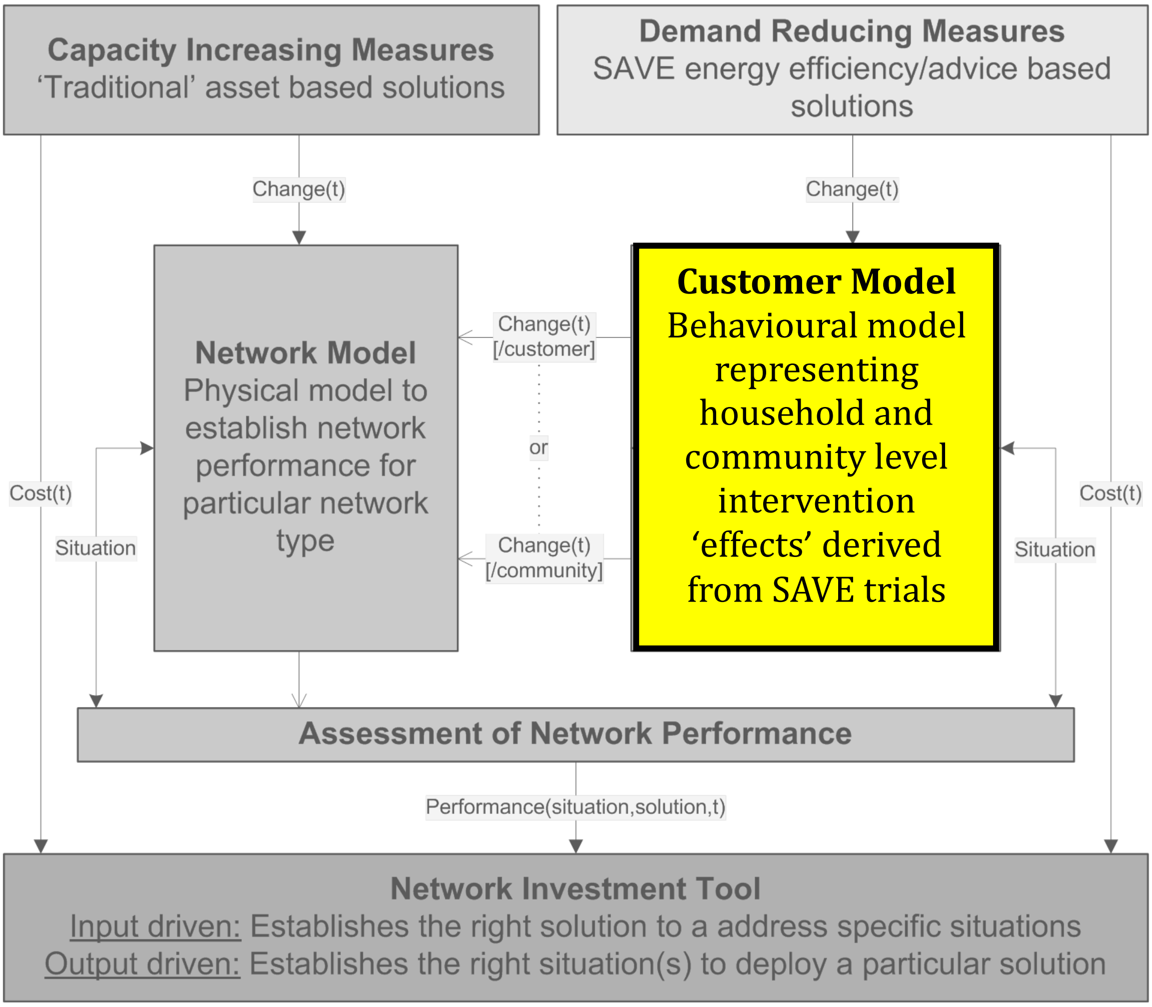

Figure 1: Overall SAVE Modelling Approach

The purpose of this report is to address Phase 1 - Model Creation and Specification. The report lays out the applied research context for the SAVE Customer Modelling Framework (SCMF) and describes its key requirements. It then outlines a modelling approach than can meet these requirements and describes its conceptual foundations and method of implementation.

In the absence of SAVE baseline data, which is to be collected from early 2015 onwards, the SCMF described here has been developed using example data to provide illustrations of the kinds of outputs that will be available in subsequent phases of development. The model will be iteratively updated with new data inputs (and thus produce new outputs) as the project progresses.

2 Research Context

Driven by the need to de-carbonise energy supplies, to reduce overall demand, to shift demand away from systemic or critical peaks and to cope with localised, time-specific and/or intermittent generation, the emerging view of smart grid future places substantial emphasis on demand-side response (DR) as a key component of a sustainable electricity system (Darby & McKenna, 2012; Jacopo Torriti, Hassan, & Leach, 2010). Whilst investigation of the technologies (Giordano, Gangale, Fulli, & Sánchez, 2013) scenarios (Xenias et al., 2014) and consumer acceptability of a range of smart grid concepts (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013) is underway, there is a clear need to develop a modelling framework which can allow regulators, policy researchers and commercial analysts to understand how particular combinations of scenarios might affect electricity infrastructures at varying levels of geographical scale and at different times of the day, week and year (Ford, McCulloch, Helfer, & Surrall, 2013).

As a recent review notes, previous work that has sought to model electricity consumption patterns at different times of day (Chrysopoulos, Diou, Symeonidis, & Mitkas, 2014) has tended either to infer consumption activities from power demand data which provides no means of knowing and thus manipulating which variants of activities and habits produced that particular 'signal', or has applied average power demand values to household appliance ownership and time of use data which provides point estimates of mean demand for stylised household activities and defined household 'types' (Aerts, Minnen, Glorieux, Wouters, & Descamps, 2014; Wilke, Haldi, Scartezzini, & Robinson, 2013). Powerful though this is, it does not allow the modelling of full demand heterogeneity over time which is crucial to appropriate infrastructure dimensioning nor does it allow the analysis of the effects of interventions along dimensions other than those through which the model is implemented.

The SAVE Customer Modelling Framework (SCMF), as laid out here, will build on these approaches by using observed power consumption data at the household level as well as for a range of appliances together with a household level model of ownership and use based on time-use surveys to produce household time-of-day electricity demand profiles. These will act as input to demand simulations at the household (micro) level whilst also supporting the flexible aggregation into many combinations of groups or household types.

The Framework will tackle two typically missing facets of state-of-the art approaches to modelling the distribution of heterogeneity within and between households over time. The first is that 'average customer type' based approaches prevent the analysis of responses by dimensions other than those embedded in the limited number of 'customer types' modelled making it impossible to assess scenarios against other social, commercial or policy relevant criteria. As noted they also mask the true extent of the heterogeneity of demand.

The second is the integration with Census-based data on the local spatial distribution of different kinds of households to provide a model that can produce not only local area demand (and potential response) 'maps' under a range of demand response scenarios but also indicators of the *range* of responses likely within different groups in a local area. These insights can then provide input to network operator infrastructure management analysis and/or local power generation planning decisions (Anderson, 2014).

The utility of such local area demand modelling is well known in public service delivery (Tomintz, Clarke, & Rigby, 2008), water (G. P. Clarke, Kashti, McDonald, & Williamson, 1997) and commercial service planning as well as a number of other sectors (Birkin & Clarke, 2011). However to date there has been relatively little attempt to develop spatially disaggregated models of electricity demand that adequately represent household level heterogeneity despite their obvious applicability to the modelling of smart/green grid scenarios especially where there is the potential need to match local generation and demand at specific times, to conduct localised reinforcement vs demand reduction cost/benefit analyses and to apply localised incentives to specific low voltage (LV) network areas. All of these are highly relevant to the SAVE project objectives and will also provide significant insights for the future development of the UK Smart Grid Working Group 'Transform' model.

The overall objective of the SCMF therefore is to develop a multilevel spatially disaggregated activity-based modelling approach to the analysis of localised temporal domestic electricity demand which will then be used to assess the local demand implications of a range of demand response scenarios in the Solent area. These will include those empirically trialed by the SAVE project but the model will also be designed to enable extension to other behavioural-based scenarios. The core data on which the model will be based will be drawn from the SAVE large scale household intervention trials. A range of outputs will flow to the Network Modelling Tool (see Figure 2) and the household level data will be combined with UK Census 2011 data to provide small area (c. 1000 households) demand profiles for the Solent region.

3 The SAVE Customer Model Framework

Figure 2 shows the overall components of the SAVE Customer Model Framework, outlining the main inputs, outputs and relationships.

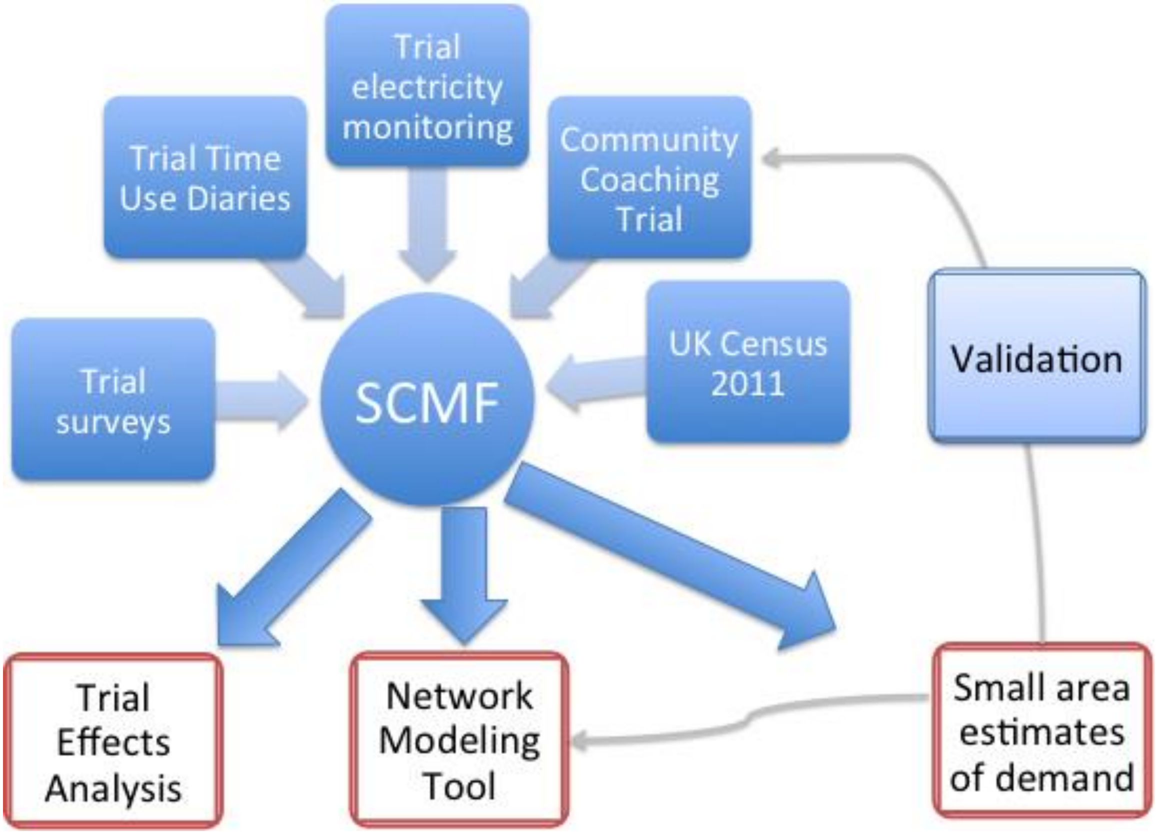

Figure 2: SCMF components and data flows

In the following sections we outline the framework's key requirements and the conceptual background to the approaches that will be employed to meet them.

3.1 Key Requirements

The SCMF has the following key requirements:

1. The ability to produce 'baseline' individual household level half-hourly electricity consumption profiles for, in principle, any day or aggregation of days of the year as input to the Network Modelling Tool;
2. To produce similar profiles for the trial intervention groups as input to the Network Modelling Tool, taking account of intervention and community trial effects where feasible;
3. To produce similar profiles for designated Census areas in the Solent area under a range of demand response scenarios including those trialed by the SAVE project;

In addition the SCMF will need to support:

4. The estimation of electricity consumption increase/decrease at specific times of day that can be attributed to the SAVE intervention trials for overall effect reporting;

5. The analysis of the household economic, demographic and behavioural factors that mediate these changes to provide insights relevant to future DNO interventions;
6. The ability to estimate changes in temporal (half hourly) demand that might ensue from other (non-trialed) behavioural changes;

Overall it is our view that these requirements can best be met using a framework that includes the following key features:

- *Microsimulation* – households will be modelled as units (micro) with specific observed consumption values rather than modelled as groups or types of households with 'average' consumption values;
- *Time-of-day* – household level consumption will be represented and analysed at the half hour level over 48/7/365 to enable analysis of scenarios which affect consumption at specific times of day and/or season – such as time of use tariff incentives or effects of LEDs on winter evening lighting use;
- *Spatial* – aggregate demand profiles for local areas will be produced by combining the microsimulation model with UK Census data to produce a *spatial microsimulation* model.

The remainder of this section introduces these features in more detail and will show how the SCMF will significantly advance a number of fields of applied energy research in the areas of:

- *Energy Demand Microsimulation* of time-use survey data through the development of appropriate methods for modelling changes in micro level time-use behaviour as a consequence of energy demand reduction interventions;
- *Energy Demand Spatial Microsimulation* through the integration of time use and census data to provide local area temporal activity or demand or activity profiles;
- *Local Demand Response scenario analysis* through the development of a novel spatially disaggregated microsimulation model of electricity demand that enables intervention or policy scenarios to be analysed at the local area level and for different populations within those areas whilst maintaining realistic distributions of demand heterogeneity.

The SCMF will therefore provide a novel customer demand scenario modelling capability for SSEPD in particular and UK DNOs in general. Apart from feeding forward into the SAVE Network Modelling Tool, it will also feed insights and methods into the UK (Workstream 3 - Developing Networks for Low Carbon) and EU Smart Grid fora as well as the European Distribution System Operators' Association for Smart Grids supported through SSEPD.

3.2 Microsimulation

The inevitable loss of information when modelling using aggregated data or average values across categories of units – such as the modelling of energy demand by household 'types' as opposed to at the household level - was first noted by Orcutt (1957). His proposed alternative 'new type of socio-economic system' set out to model social and economic processes at the unit (e.g. single persons or households) rather than the aggregate level by applying models of change to the units themselves. The approach, now termed micro-simulation, has been mainstreamed in the transport, health and especially tax, benefit and pension modelling contexts (Mitton, Sutherland, & Weeks, 2000; Robert Tanton, Vidyattama, McNamara, Vu, & Harding, 2009; Zaidi, Harding, & Williamson, 2009), especially where a fixed set of rules (e.g. tax or price changes) can be applied to a large heterogeneous population to understand the distributional effects of potential change. In most cases to date this 'distribution' has been financial such as the distributional effect of tax changes on household incomes or price changes on energy demand (Baker, Blundell, & Micklewright, 1989; Baker & Blundell, 1991). However interest is growing in the development of microsimulation models which examine distributions of outcomes across time (e.g. time of day) for different kinds of households following other kinds of interventions (Zuo, Birkin, & Malleson, 2014) or in the context of urban heat systems (Peters, 2014).

Microsimulation models function by taking a large scale dataset of the units of interest, such as a household electricity demand survey, and applying a range of methods to model potential changes to any attributes at the individual unit level that are thought to affect the outcome of interest. These might include factors affecting evening electricity demand such as labour market participation, media-use choice or laundry and cooking habits.

Variations within this general approach include:

- the use of static micro-simulation approaches to alter the attributes of the modelled units and impute consequential changes in outcome distributions across different household types (Ballas et al., 2005; Mitton et al., 2000);
- the use of dynamic and/or event driven approaches to model changes to the population units over time using a range of empirically derived 'transition' probabilities. This includes the modelling of potential behavioural responses to interventions and/or change (Anderson, De Agostini, & Lawson, 2013; Birkin & Clarke, 2011);
- the combination of survey with census data to construct representative but synthetic whole population data sets for small area analysis (P Williamson, Birkin, & Rees, 1998). The application of these approaches to water demand modelling suggest that an increase in overall demand would not be spatially uniform with local area increases ranging from 10-45% implying the need for local area infrastructure investment or preventative intervention (Paul Williamson, 2001) just as is currently being proposed in the LV network context.

Critically, in all cases each unit is modelled as a distinct entity so that full heterogeneity to be found 'in the real world' can be maintained. Average consumption values, with appropriate estimates of variation and/or uncertainty for different household types for a range of scenarios therefore become a way to *represent results and to reveal group level distributional effects (or change)* rather than being core components of the models themselves. The focus on the unit level and recent increases in computing power have brought implementation methods such as agent-based systems to the fore, especially where dynamic processes between the units are required (Wu & Birkin, 2012).

Two recent volumes provide an excellent range of examples of all three forms of microsimulation mentioned above (Gijs Dekkers, Keegan, & O'Donoghue, 2014; Zaidi et al., 2009). These include static microsimulation models to estimate future changes to household derived greenhouse gas emissions under a range of policy scenarios; to estimate future temporal demand for household heating in decentralised urban energy grids (Peters, 2014) and to model demand for a range of public and retail services. Further, as discussed below the combination of such models with a number of 'spatialisation' techniques has recently provided the means to construct models of local area demand which can be used as inputs to localized infrastructure investment cost-benefit analyses (Birkin & Clarke, 2011).

In summary, for the purposes of the SCMF, the microsimulation approach implies the analysis and modelling of household (micro) level data with aggregations to segments, types or groups used only for results reporting or dissemination purposes. Interventions or scenarios will therefore be applied and modelled at the individual household level and, in this case, initially using a static microsimulation approach. The SCMF will therefore model the 'effects' of the interventions or other change scenarios (see below) on a household's electricity demand profile. Processes of ongoing social or demographic change will only be implemented where they are defined in a demand response scenario – such as an intervention uptake model. Whilst including such processes is attractive in terms of constructing future customer projections it would imply the need to include models of social change, household transformation, changes to and uptake of new energy consuming devices and changes to consumption habits. Such modelling is well known to require substantial resources (Zaidi et al., 2009) at a level that are beyond the capacity of this project.

3.3 Modelling time of day consumption

There have been a number of attempts to model domestic half-hourly (or finer-grained) energy consumption of which most are based on stochastic appliance use models (Jacopo Torriti, 2014). Some have also incorporated aspects of routine energy use or attempted to model the temporal nature of demand (McLoughlin, Duffy, & Conlon, 2012; Richardson, Thomson, Infield, & Clifford, 2010; J Widén, Lundh, & Vassileva, 2009) either through probability-based models based on measured energy use or derived from appliance time of use data (Yao & Steemers, 2005).

There have also been a number of recent attempts to more directly base such models on time-diary data (Ellegård & Palm, 2011; Palm & Ellegård, 2011; J Torriti, 2012; J Widén et al., 2009). In this case patterns of electricity consumption are imputed using the range of activities recorded in the time use diary at specific times of the day. The 'demand' implied by these activities is imputed through reference to existing data on the average energy intensity of different appliances. Whilst a number of these models have produced validated results (see for example (Joakim Widén & Wäckelgård, 2010)) especially where household occupancy is the key outcome, more recent work has highlighted the extent to which this method may or may not be valid for different appliances in different contexts (Durand-Daubin, 2013). For example Durand-Daubin suggests that imputing the electricity consumption of washing machines, TVs and computers from time-use diaries is difficult as all of them may be 'demanding' electricity even though they are not being directly used and thus not reported as such in a diary. TVs are regularly left 'on' (not just in standby) when not being actively watched and the same is true for personal computers. In the case of washing machines the time use diary data may record the act of filling and switching on and then the subsequent emptying of the machine, but not the period in between when electricity is actually being used.

This can be observed in Figure 3 which shows the half hourly distribution of laundry as measured by the ONS 2005 Time Use Survey (Office for National Statistics, 2005) and 'washing/drying' as reflected in the Home Energy Study dataset (Zimmerman et al., 2012).

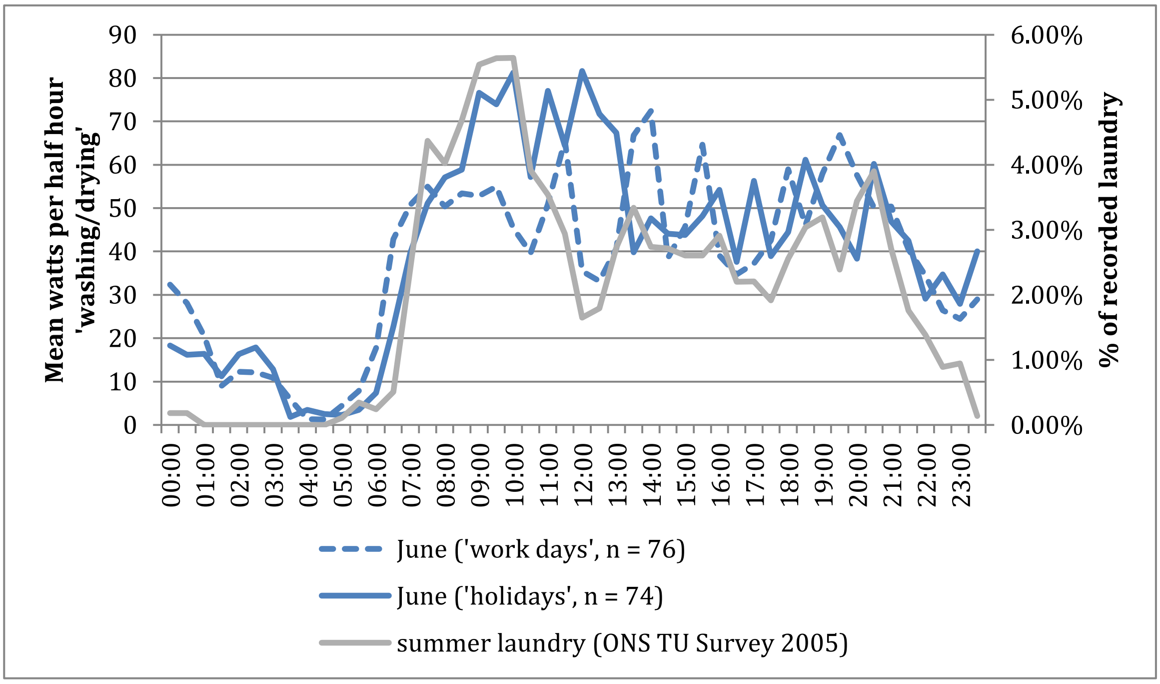

Figure 3: Mean watts per hour used for washing/drying (Source: Author's calculations using DECC"s Household Electricity Survey data available from https://www.gov.uk/government/publications/spreadsheet-tools-for-users) and % of reported laundry (Source: Author's calculations using UK Time Use Survey 2005, summer 2005, weighted)

Although the HES data includes both clothes washing and dish-washing and relates to owner-occupied dwellings only and the time-use data does not (here) distinguish between weekdays and 'holidays', the electricity demand curve for washing/drying broadly matches that reported in the time-use data, especially in the early morning. The later evening disparity can be explained by the presence of dishwasher use in the HES data. However we might conclude that the ongoing electricity demand by washing machines as they run in mid-morning is poorly captured by the time use survey as respondents record subsequent activities or even leave the home.

A further complication is the need to aggregate time-use and appliance usage data for multiple members of a household (Jacopo Torriti, 2014) in order to more accurately build an overall demand profile. Whilst some studies side-step this issue by focusing on single person households (J Torriti, 2012) this is clearly not sufficient for an entire population or customer base study. This has implications for base data collection since time use diaries frequently capture data from only one person per household due to difficulties of response and cost.

Nevertheless there has been considerable discussion of the potential utility of such time-diary based approaches in modelling future scenarios of demand response (Jacopo Torriti, 2014; Joakim Widén & Wäckelgård, 2010). The linkage of activities to appliance power demand to duration and time-of-use provides a mechanism through which scenarios involving factors such as greater appliance efficiency, reduction in duration or time-shifting of use can all be implemented.

As Torriti's review suggests the combination of temporal data with customer information can provide both TNOs and DNOs with useful information on the household behaviours that lead to the aggregated demand profiles that are observed in the residential parts of LV networks (Jacopo Torriti, 2014). Thus, if suitable time-use diaries can be developed which make it easier to distinguish between active and 'passive' appliance use and which can associate both appliance level and household level demand with recorded activities for as many household members as possible then a powerful modelling framework would be in place. As Torriti notes, such an undertaking is complex and few studies to date have been able to use the kind of large scale representative population sample survey data to be collected by SAVE to produce generalizable results, let alone incorporated evidence-based modelling of a range of demand response interventions.

In summary, the time-diary based approach offers considerable power in enabling demand response to be modelled at the household level through the manipulation of assumed energy efficiency and the prevalence, timing and duration of activities. In implementing such a model using the innovative tightly integrated data to be collected during the project, the SCMF will provide a powerful infrastructure for the analysis of demand response scenarios.

3.4 Spatial Microsimulation

Recent years have seen an increasing demand for the development of small area (i.e. neighbourhood level) estimates of a range of socio-economic indicators not only for research and public policy use but also for commercial applications (Rao, 2003). In the case of public policy they may be required as part of a needs assessment for locally-targeted resource allocation or policy interventions in fields such as poverty (Birkin and Clarke, 1989, Williamson and Voas, 2000, Tanton et al., 2011, Gong et al., 2011), health (Ballas et al., 2005, Mohana et al., 2005, Smith et al., 2007, Morrissey et al., 2008, Edwards and Clarke, 2009) or natural resource use (Williamson, 2001, Druckman and Jackson, 2008). In the commercial context small area estimates of the prevalence of certain social groups or consumption patterns are commonly used as part of direct marketing activities; in cost/benefit analyses for investment decisions in retail, service or other infrastructures (Hanaoka and Clarke, 2006, Nakaya et al., 2007, Anderson et al., 2009, Birkin and Clarke, 2011) as well as in the assessment of local market size for small businesses (Rao, 2003). In general such small area estimates respond to the need to produce statistics for areas where survey sample coverage is either non-existent or is considered too small for robust direct estimates to be made or where geo-demographic classification approaches are found to be unreliable (Voas & Williamson, 2001).

In response to this demand a range of approaches to the estimation of household characteristics at small area levels using both model based (Bates, 2006, Rao, 2003, Gosh and Rao, 1994, Elbers et al., 2003, Molina and Rao, 2010, Esteban et al., 2012, Marchetti et al., 2012) and so-called 'spatial microsimulation' or survey re-weighting approaches (Anderson et al., 2013; Birkin & Clarke, 1989; Gong, McNamara, Vidyattama, Miranti, & Tanton, 2011; R Tanton, Vidyattama, Nepal, & McNamara, 2011; P Williamson, 2005) have been developed.

Birkin and Clarke showed that an iterative proportional fitting (IPF) reweighting approach (Norman, 1999; Simpson & Tranmer, 2005; Wong, 1992) offered considerable potential for the creation of synthetic small area microdata through the re-weighting of national or regional survey microdata, such as a sample survey, using data from the Census of population. Put simply the method allocates all households from the sample survey to each small area and then, for each small area, iteratively re-weights each household so that the derived small area level tables of aggregate statistics for those re-weighted households match identical tables from the UK Census 2001 (Birkin & Clarke, 1989; P Williamson et al., 1998). This re-weighting requires the identification of suitable constraint variables that must exist in both the small area (Census) and survey data in identical form. It is these constraints that are the subject of the re-weighting (fitting) process.

Building on this work Ballas et al (1999) tested a number of approaches to the estimation of small area level trends in income in York and Leeds between 1991 and 2001 using a combination of Census and British Household Panel Survey (BHPS) data (Ballas, 2004). He concluded that the IPF method was preferable on a number of dimensions including its deterministic nature and relatively efficient algorithm. Recent work has sought to improve on these initial approaches through the further refinement of methods of error estimation (Smith et al., 2009), the selection of small area constraints (Chin et al., 2005, Birkin and Clarke, 2012, Anderson et al., 2009) and the use of a range of re-weighting techniques (Tanton et al., 2011, Gong et al., 2011).

In summary a range of approaches to the small-area estimation of household attributes have been developed. With a few exceptions (Anderson, 2014) they have rarely been used to estimate the distribution of energy demand at small areas, as opposed to Local Authority level (Zuo et al., 2014) and none have sought to produce estimates of temporal profiles. The SCMF will therefore build on Birkin and Clarke (1989, 1988b) and Ballas et al (Ballas et al., 2005) by using the well-known iterative proportional fitting (IPF) algorithm to develop a survey-reweighting approach to the estimation of small area temporal energy demand profiles under a range of scenarios.

3.5 Integration with Community Trial

Whilst there are considerable and significant methodological differences between the SAVE Community Intervention trial and the three household level trials which form the spine of the SAVE Customer Model we have the aspiration to integrate findings from the Community level study regarding the relative strength and sustainability of collective behaviour change, into the SAVE Customer Model.

Whilst the mechanism for achieving this integration is currently unclear our intention is to explore approaches that can include area-level 'community effects' derived from the Community study in the Customer Model. Whilst this is a known method in statistical multi-level modelling its application in this context it relatively novel and this is especially so where not all required 'community types' may be represented in the Community study. This integration should therefore be seen as experimental.

4 Overall Model Framework

As shown in Figure 2, the SCMF will take the following inputs:

1. Household socio-economic and demographic data from the recruitment and then repeated waves of household surveys including appliance ownership and energy using habits;
2. Household response person time-use activities as recorded at 10 or 15 minute intervals in a 1-day time-use diary to be implemented as part of the repeated waves of fieldwork;
3. Dwelling level electricity consumption data (in kWh) provided by Maingate plc at the ½ hour level by default and at the 10 or 15 minute level during the period of time time-use diary;
4. For a sub-sample of the households, selected appliance level electricity consumption data provided via Maingate's smart plugs;

Suitably anonymised versions of these datasets will be held at the University of Southampton for the purposes of analysis and model development.

The SCMF baseline model will comprise a representation of all 'trial' households in complete form as units by linking this data. Table 1 shows the basic framework (using synthetic data) for the linked data on the day that the household response person (HRP) in household ID=12 completed a time-use diary. From this we can see that the person followed a fairly standard 'morning routine' which included a shower (primary act [P_ACT] = shower at 07:10) which resulted in an increase in electricity demand [METER]. Eating (07:20 – 07:40) used less electricity and the diary also recorded listening to the radio (secondary act [S_ACT]) but at 07:40 the HRP loaded and started the washing machine producing a measured trace from the washing machine smart plug [W_M] and an associated increase in overall kWh [METER]. The LOCATION entry for the diary indicates that the respondent was at home until 07:50 when they started to travel.

Although not shown in Table 1, the full range of survey derived attributes of the household will be linked to this data via the HH_ID. Were we to do so we might learn, for example, that this household was occupied by a single person aged 25-34 in full time employment and was in intervention group 2. Using these characteristics the SCMF will therefore support the analysis of the complete dataset through aggregation of electricity consumption data by trial group, by designated household types and/or by clusters that emerge from analysis of the electricity consumption data itself.

Crucially the period when the time-use diary is recorded enables the direct linkage of activities in the home with variation in electricity demand both at the overall meter level and, through the smart plugs, selected appliances.

Table 1: Exemplar model data rows for an imaginary single person household

HH_ID	DAY	TIME	P_ACT	S_ACT	LOCATION	METER	TV	W_M
12	13-Nov-15	07:00	sleep	not recorded	home	0.3	0.001	0
12	13-Nov-15	07:10	shower	not recorded	home	1	0.001	0
12	13-Nov-15	07:20	dress	listen to radio	home	0.4	0.001	0
12	13-Nov-15	07:30	eat	listen to radio	home	0.6	0.001	0
12	13-Nov-15	07:40	eat	wash clothes	home	2.2	0.001	2
12	13-Nov-15	07:50	travel	listen to radio	elsewhere	1.4	0.001	1

This model framework will therefore be a way to represent the 'observed' data from the project baseline period and will enable the straightforward statistical comparison of patterns of demand between different kinds of households in order to support the refinement of trial interventions (WP4).

As new data enters the SCMF following subsequent surveys, trial interventions and ongoing consumption monitoring it will then be possible to provide descriptive analysis of the differences in terms of overall and time-of day demand between the trial groups before and after the interventions.

The SAVE team will then be able to use insights from this analysis to iterate the trial designs based on a knowledge of which kinds of households appear to be responding more or less to the interventions. In turn this will also enable SSEPD and other DNOs to undertake cost/benefit analysis of the likely return on investment of such interventions not just 'on average for the entire customer base but for specific kinds of customers and the model may also provide a means to identify these customers using ½ hourly consumption data (i.e. future smart meter data) alone.

Finally, the framework will also provide the basis for the development of spatial (local area) estimates of demand by combining this data with UK 2011 Census tables at the Lower Layer Super Output Area Level[1] using the IPF-based spatial microsimulation approach outlined above. If these estimates are based on the baseline (control) group then they will provide 'business as usual' estimates. However if they are based on the intervention groups then they will provide estimates that simulate the roll-out of the intervention to all areas in the SAVE region.

5 Model development stages

The overall SCMF will be developed in three phases:

1. Model Creation and Specification (Delivery: December 2014)
2. Baseline Model: (Delivery: December 2016) – to include initial waves of data collection and pre-trial baseline;
3. Final model: (Delivery: June 2018) – to include subsequent waves of data collection and post-trial results.

In each phase the model will be implemented in a series of stages that we describe below.

5.1 Model setup

The first phase will make use of the linked 15 minute power demand and time-use survey data from the sample of over 4,000 SAVE households. This will be used to develop a set of *appliance<->time use activity<->time<->power-demand* tuples for each household at 10 or 15 minute intervals (see Figure 2 and Table 1). The data will be held as separate but linked tables which can be brought together for analysis and simulation.

[1] Census areas covering c. 800 households, see http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/super-output-areas--soas-/index.html

5.2 Trial Data Analysis

In this stage statistical analysis detailing the range of demand profiles by defined household type will be conducted and, in phase 3 (Final model), analysis of the post-intervention data will be conducted.

As an example Figure 4 shows hypothetical results for mean kWh consumed during the evening peak at three time points. As we can see demand for the control group is slightly higher at time 1 compared to the baseline and lower at time 2 although the error bars suggest no significant difference. On the other hand the two intervention groups show substantial change and the error bars indicate that this may be statistically significant at time 2.

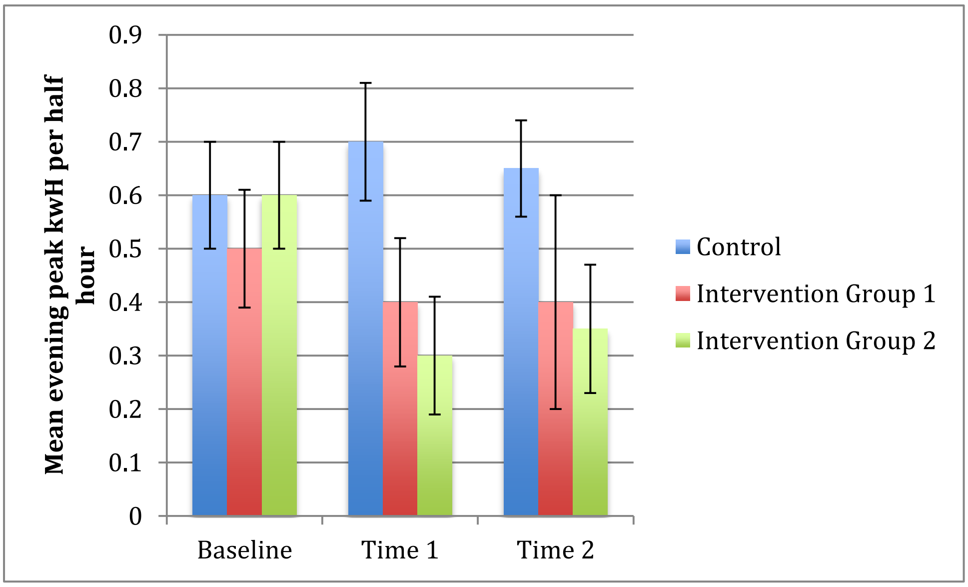

Figure 4: Hypothetical baseline and repeated measures illustrating the potential effects of 2 interventions compared to the control group. Error bars indicate 95% confidence intervals.

In contrast to most current approaches to modelling electricity demand the data will not be collapsed to average 'household types' and average 'activity power demand'. Rather, following the tenets of microsimulation modelling outlined above, the household level data will be used as input to a multilevel micro-econometric model associating a range of household characteristics, including the sequence and timing of recorded time-use activities, with the 15 minute level power demand by appliances and of the household as a whole as recorded at the household meter. This approach will then support a *difference-in-difference* analysis to establish the overall and time-of day demand effects of the SAVE intervention trials whilst also statistically controlling for other confounding factors such as household demographics or habits.

Figure 5 shows the hypothetical results of such a model. Here, the change over time for each group are contrasted (difference in differences) and can be adjusted using the econometric model to control for household characteristics. This analysis would confirm that both interventions had a significant effect by time 2 and that intervention 2 had the biggest (and most uniform) effect. However intervention 1 was no longer significantly different from the control by time 3. Clearly the chart shows the 'average' effect for all households in each group, however the modelling process could also be used to test if the changes are larger or smaller for specific household types within each group.

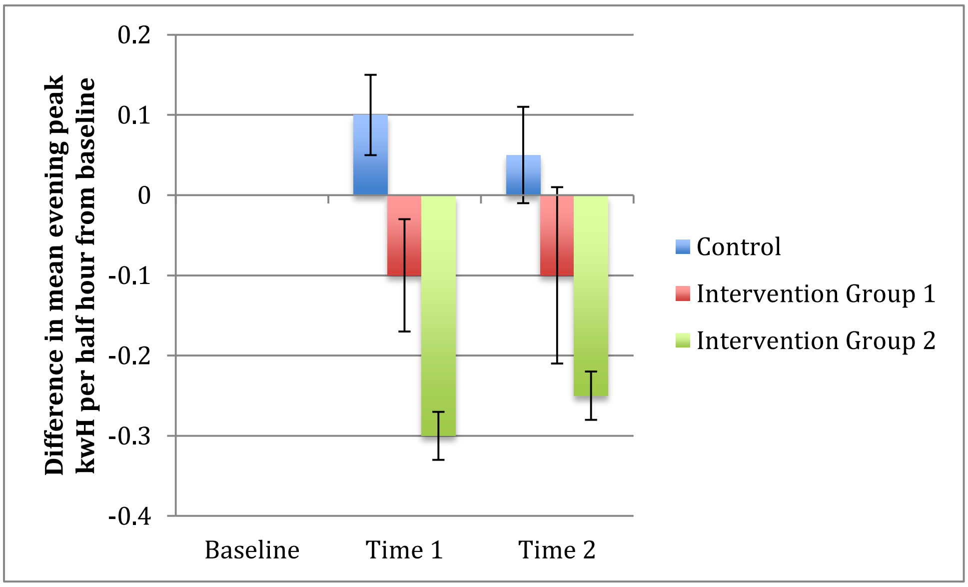

Figure 5: Hypothetical adjusted difference in difference measures illustrating the potential effects of 2 interventions compared to the control group. Error bars indicate 95% confidence intervals.

Analysis will also be undertaken of the relationship between time-use activities, appliance level and household level electricity consumption in order to provide insights for potential demand scenario modelling as well as suitable inputs to the Network Modelling activity.

5.3 Experimental Microsimulation

Whilst the main objective of this stage would be to develop a microsimulation of the effects of the three large scale trial interventions, it should be noted that the *appliance<->time use activity<->time<->power-demand* tuples allow a range of other scenarios to be modelled. These could include:

1. changes to the efficiency of the appliance – so that a given appliance use might consume less electricity;
2. changes to the timing (and duration) of activities/appliance use – so that, for example, TV watching might be delayed to later in the evening;
3. normative shifts in the timing of activities or changes to constraining socio-structural factors (such as employment hours and travel times);

Alongside the trial-based models, this stage will also see the definition and implementation of a small number of exemplar 'scenarios' selected from amongst these options based on insights derived from the analysis stage.

These will be implemented using the multilevel micro-econometric model referred to above and will produce a similar set of household level demand profiles under different scenarios which can also act as inputs to the Network Model.

5.4 Spatial Microsimulation

This stage will use an IPF-based spatial microsimulation approach (Anderson, 2013; Birkin & Clarke, 2011; Birkin & Wu, 2012) to integrate the large-scale household level microsimulation model (n>4,000 households) with UK Census data for 2011 to produce:

1. A synthetic Solent region micro-data household 'energy census' dataset representing the baseline temporal electricity demand characteristics of all households in each of the 1,137 UK census Lower Layer Super Output Areas (LSOA) in the Solent region.
2. Aggregated temporal (30 minute) demand profiles (together with appropriate measures of within-area profile heterogeneity) for each LSOA. Of particular interest will be correlations between estimated temporal load profiles and actual load profiles recorded by the sub-station monitoring component of the SAVE community trials;
3. A range of temporal (15 minute) mean and total power demand profiles based on the scenarios defined in 5.3 forming estimates of the local area consequences of the demand response scenarios. These results will be provided as input to the Network Modelling activity should customer demand profiles for specific Solent region locations be required.

5.5 Outputs Summary

Overall, this framework will therefore produce several kinds of outputs:

1. A flexible modelling framework for use in subsequent stages;
2. A flexible analytic framework to support analysis ongoing in WP4;
3. Baseline, post-intervention and behavioural change scenario demand profiles (48/7/365 if required) as input to the Network Modelling tool;
4. Estimates of average baseline, post-intervention and behavioural change scenario demand profiles (48/7/365 if required) for all LSOAs in the SAVE region as an input to the network modelling tool if required and for use in validation against the sub-station monitoring being conducted in the SAVE community intervention trial.

6 Technical implementation

Given its complexity, the modelling framework will be implemented using a statistical software package such as STATA or, more likely, R. This will provide the ability to input, link and analyse the household level temporal energy consumption, time use and survey-derived data. The anonymised data will be held in a secure relational database at the University of

Southampton and will be extracted and linked using the statistical software package as needed for analysis and model development.

The core of the model will be implemented as 'open source' statistical scripts which will be archived via a public github repository with appropriate licensing terms within the context of the overall LCNF and SAVE project intellectual property framework.

Support for the re-use of the modelling framework outside the SAVE project will therefore be enabled by:

- Support for the re-use of the model statistical scripts using the anonymised SAVE trial data which is to be submitted to the UK Data Service at project completion. In this case a user (such as another DNO) would register with the UK Data Service and agree to the terms of use in order to download the data. The statistical scripts constituting the model would be available for re-use via github.
- Support for the modification of the model statistical scripts for use on a bespoke dataset by a DNO or other user. In this case the user would download the scripts from github and, with full attribution as specified in the license terms, modify them for their own purposes.

7 Dissemination tool

Reflecting the complexity of the SCMF, the final phase of model development will be the implementation of a web-based data analysis and dissemination tool. Whilst the requirements for this tool have yet to be fully specified, it is envisaged that this tool will enable any interested party to conduct a limited range of analyses using the SAVE data. These analyses are likely to include:

- the generation of summary tables and/or graphs of temporal load profiles for a range of pre-determined household types or groups under the different trial intervention conditions for specific seasons or periods;
- the generation of maps of the estimated distribution of similar temporal load profiles at the LSOA level for the Solent region.

Support for the downloading of summary tables wouild be included under a suitable attribution license.

8 Exemplar Results

In the absence of SAVE household data this section provides examples of the kinds of analysis outputs[2] that will be supported by the SAVE Customer Model Framework.

[2] The statistical scripts (but not the data) used to generate these results can be downloaded from: https://github.com/dataknut/SAVE/tree/master/WP2-CustomerModel

8.1 Time Use Survey Analysis

As outlined in Section 3.3 time-use surveys have been increasingly used as the basis for temporal demand modelling. In addition, recent work has started to use this form of data to understand the temporal nature of the social practices which drive demand profiles (Shove & Walker, 2014; Walker, 2014). Of particular interest has been the analysis of the components of 'peak' demand to provide insights for the consideration of demand response interventions (Anderson, Torriti, & Hanna, 2014; Powells, Bulkeley, Bell, & Judson, 2014; Jacopo Torriti, 2014).

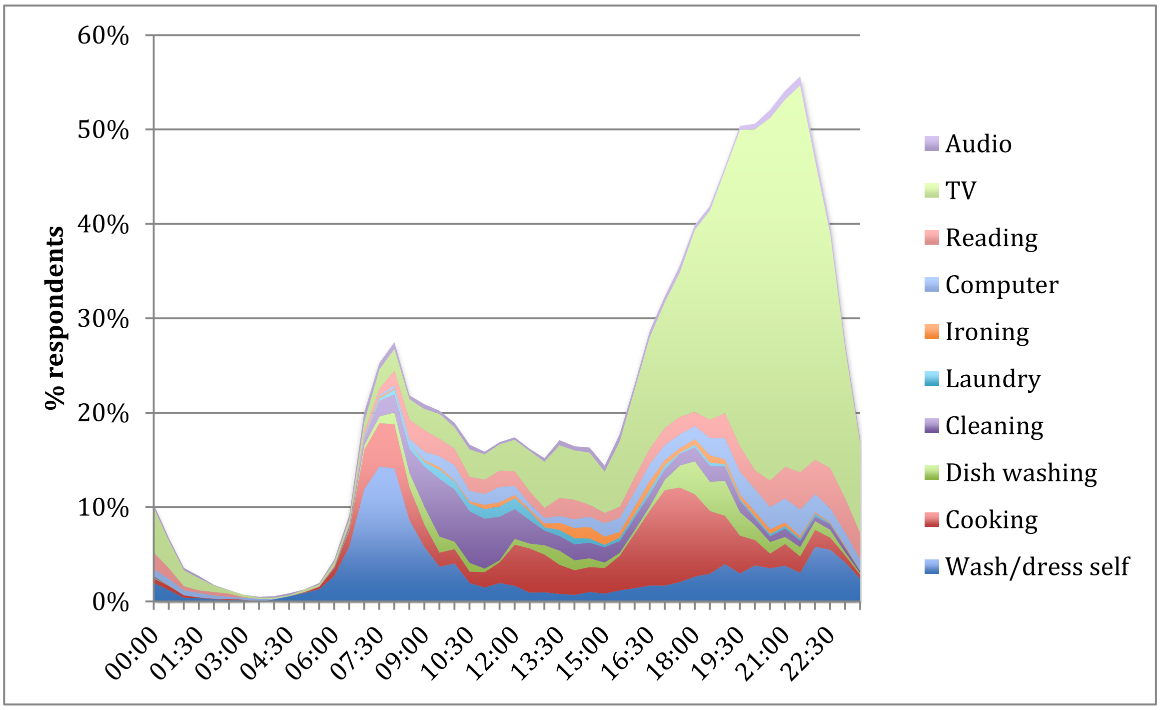

Figure 6: % of respondents aged 25-64 reporting a selection of energy-demanding activities (Source: Author's calculations using UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

As an example Figure 6 shows the percentage of respondents to the UK 2000/1 Time Use Survey (Ipsos-RSL and Office for National Statistics, 2003) aged 25-64 who reported a selection of energy demanding activities at different times of the day on weekdays in the winter. This chart not only replicates the well-known overall household electricity demand profile but it starts to provide insights into the drivers of peak demand – such as washing and cooking in the early part of the day and cooking and media use later in the day.

It therefore illustrates how Stage 2 (Trial Data Analysis) of the modelling phases can provide insights into the drivers of peak demand which can feed into the iterative design of interventions. The analysis of post-intervention data will then enable the analysis of what habits might have changed through analysis of changes in the time-use data and may therefore be able to explain any changes in measured consumption.

8.2 Imputing demand and microsimulation based scenario modelling

Whilst the analysis shown in Figure 6 reports the results for the whole population, the (micro) household level nature of the data supports the analysis of distributions for different population sub-groups. When combined with a simple model linking electricity demand from activities as will be done in Stages 2 & 3 (Trial Data Analysis & Experimental Microsimulation) this will enable us to examine the difference between modelled load profiles for different kinds of households.

As an example we have used the SCMF and the UK 2000 Time Use survey (which interviewed all persons aged 8+ in the household, (Ipsos-RSL and Office for National Statistics, 2003)) to implement a much simplified version of the model described by Widen et al (J Widén et al., 2009). The model ascribes power demand to activities that were recorded at home in 10 minute time slots according to the parameters given for Model 1 in Table 2. Clearly these values are imperfect and allow only for the imputation of 'instant' power demand based on the current activity. No attempt has been made to model lagged energy demand (Joakim Widén & Wäckelgård, 2010) following an activity (e.g. washing machine use) or to adequately account for the 'washing' component of 'wash/dress' other than through a 25% allocation (see Table 2).

Table 2: Power demand assumptions in baseline demand imputation model

Time-Use Category	Model 1		Model 2	
	Watts per 10 minutes	Notes	Watts per 10 minutes	Notes
Washing/ Dressing self	525	Assumes washing self = 1/4 of a 10 minute slot of 'wash/dress' with instant electric hot water demand (e.g. electric shower)	0	Scenario of non-electricity hot water heating
Cooking	1500		1500	
Dish washing	430	Assumes all dish-washing done using dishwasher	430	
Cleaning	1000		1000	
Laundry	490	Drying cannot be distinguished in the time use data	490	
Ironing	1000		1000	
Computer	100		100	
Reading	80		80	
TV	200		200	
Audio	100		100	

The values were used to impute individual level demand for each 10 minute time period for each diary respondent before aggregation to the household level for half-hours. All power demand was summed, thus assuming concurrent appliance use with the exception of cooking, laundry and dish washing for which the largest value (maximum) across the individuals in the household was taken thus assuming multiple persons used a single appliance if these activities were recorded at the same time. In the case of TV use in particular this is likely to overestimate evening electricity demand as the model assumes all concurrent TV watching is done on different appliances. The approach used to model 'washing self' will also over-estimate electricity demand as it assumes a fraction of 'wash/dress' is always using hot water that is (instantaneously) heated using electricity. However, the details of the model are less important than the principle (and can easily be altered as the SAVE data and evidence base develops). Figure 7 shows the resulting mean household electricity demand profile for weekday half-hours in the winter of 2000/1 by the number of earners in the household.

We have specifically chosen to report the results according to the number of earners, not because it has particular analytic value but because it emphasises that the results of a microsiumulation model can be aggregated and reported according to any dimension present in the original micro (survey) data set. To re-iterate, we have not applied the power consumption values to 'the average' activities at each half hour for the 'average' zero, single, 2 or 3+ earner households. Instead we have taken data of the form shown in Table 1 and applied the power demand values to each activity reported by each individual in each 10 minute section of the diary. We have then aggregated the demand to the household level before presenting means according to a characteristic of the household.

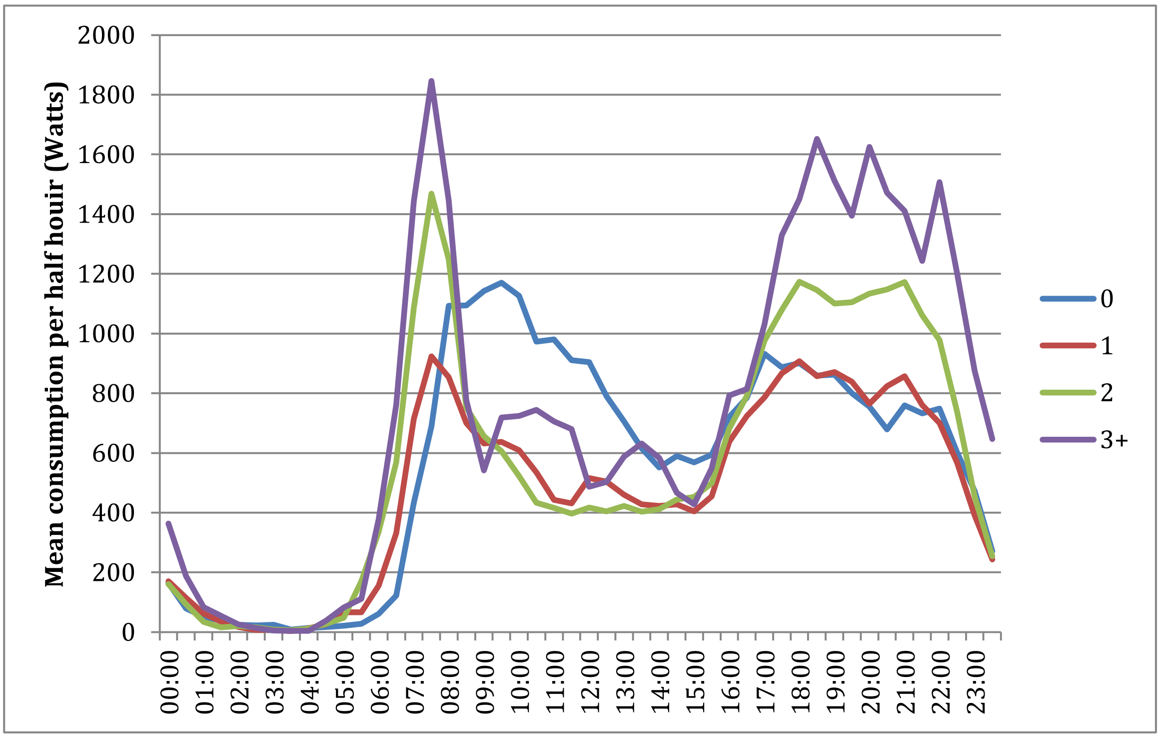

Figure 7: Model 1 imputed mean half-hourly household electricity demand by number of earners (Source: Author's calculations using UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

As we might expect the model suggests that households with no earners do not exhibit a weekday 06:00 – 08:00 morning peak and the more earners there are, the higher the consumption in the evening.

Altering the parameters of the model slightly enables us to examine the scenario (Model 2 in Table 2) where no electricity is used to heat hot water for washing – for example where gas or some other fuel is used. The results of re-running the model under these new parameters are shown in Figure 8. As might be expected the model suggests a notable decrease in the early morning demand peak and also ameliorates demand later in the evening without recourse to assumptions about behavioural change. As noted above, the exact parameters and their plausibility are not important to this discussion but serve to illustrate the way in which the SCMF enables scenarios to be developed at the micro (individual or household level) and then aggregated according to dimensions of interest.

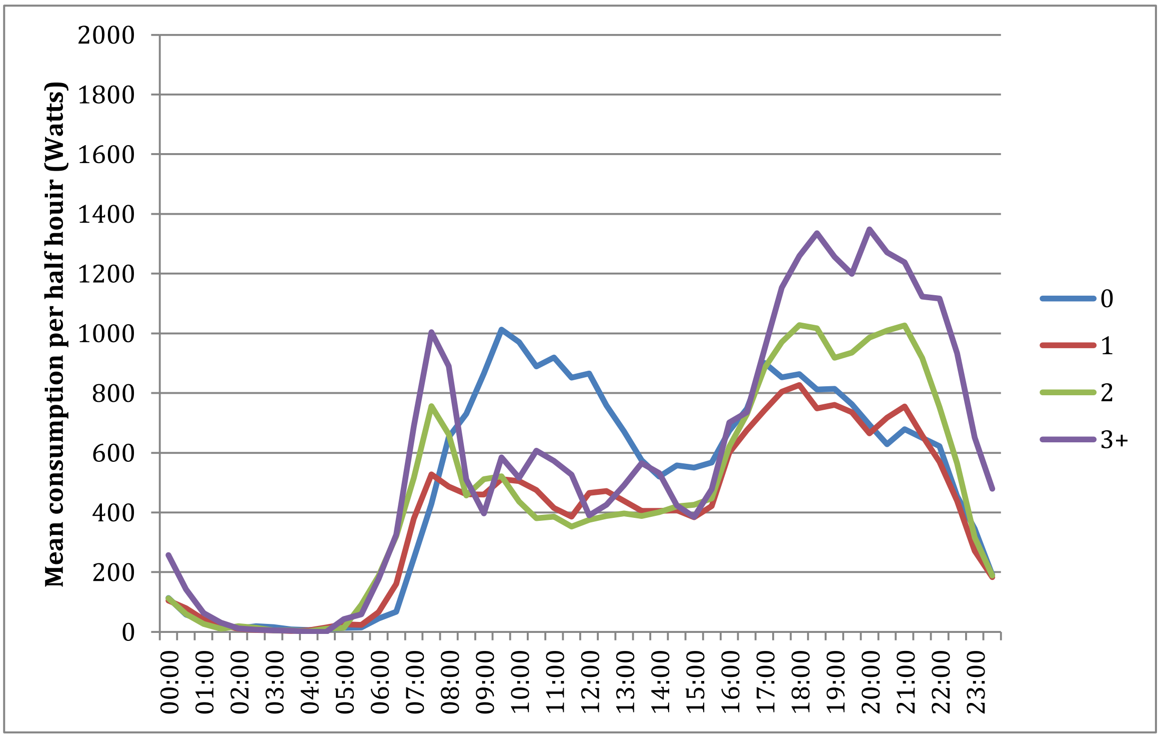

Figure 8: Model 2 imputed mean half-hourly household electricity demand by number of earners (Source: Author's calculations using UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

Figure 9 on the other hand shows the imputed total consumption by number of earners calculated by summing the modelled power demand for all households of each type. Clearly households with 3 or more earners are relatively rare so that even though their mean consumption is higher (Figure 8) their contribution to overall demand is relatively low. In addition whilst dual-earner households are modelled to use less during the day, perhaps due to joint absence from the home, they appear to use proportionately more in the evening.

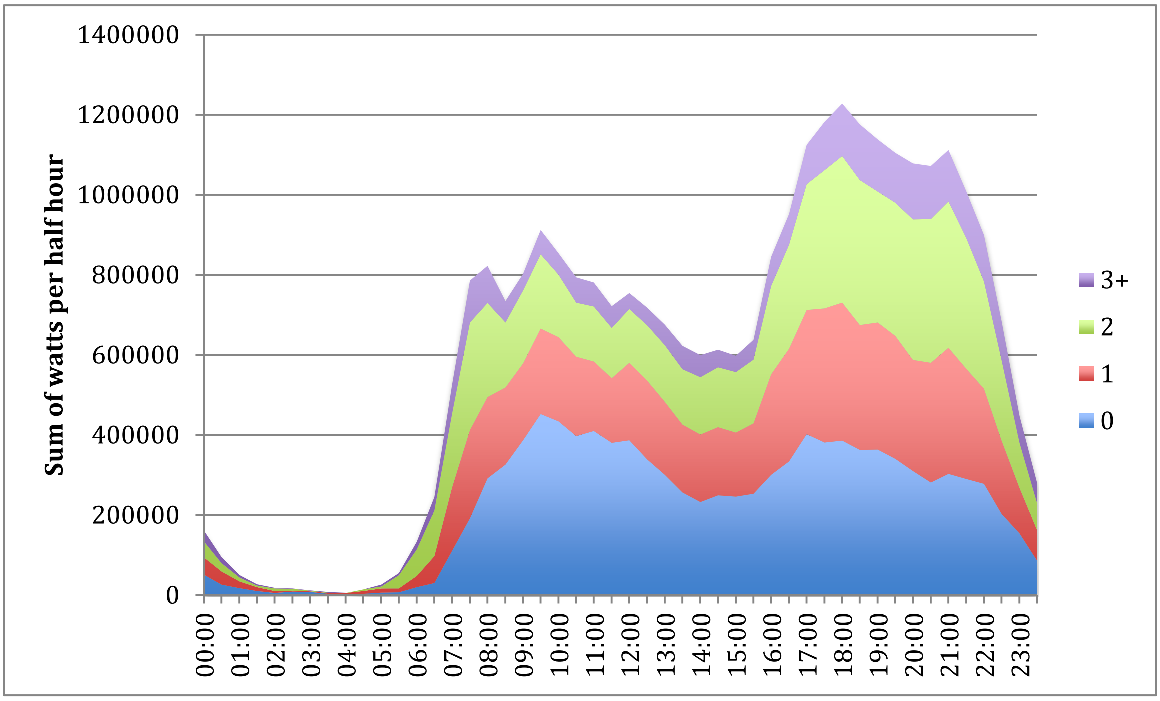

Figure 9: Model 2 imputed total half-hourly household electricity demand by number of earners (Source: Author's calculations using UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

The overall time-use survey to be conducted as part of the SAVE project will support similar analysis but crucially, as Section 5.1 makes clear, activities will be linked to appliance and household level electricity consumption monitoring to overcome the kinds of mis-alignment problems discussed above (c.f. Durand-Daubin (2013)) and avoid the need to make substantial assumptions about the power demand of different activities.

8.3 Small Area Estimates of Electricity Demand Profiles

Finally, in order to demonstrate the utility of the methods discussed under Stage 3 (Spatial Microsimulation), we have combined the results of the above microsimulation with UK Census 2001 small area data for the Southampton area using the IPF-based spatial microsimulation approach outlined above to produce half hourly mean demand profiles for each LSOA in Southampton under Models 1 and 2.

Figure 10 shows the same graph as Figure 9 (total power demand) but for E01017139 (Southampton 029A) under Model 1 power demand assumptions. E01017139 was the LSOA with the highest proportion of households with no earners in Southampton according to the UK Census 2011. Figure 11 shows same results but for E01017180 (Southampton 002A), the LSOA with the lowest proportion of households with no earners in Southampton according to the UK Census 2011.

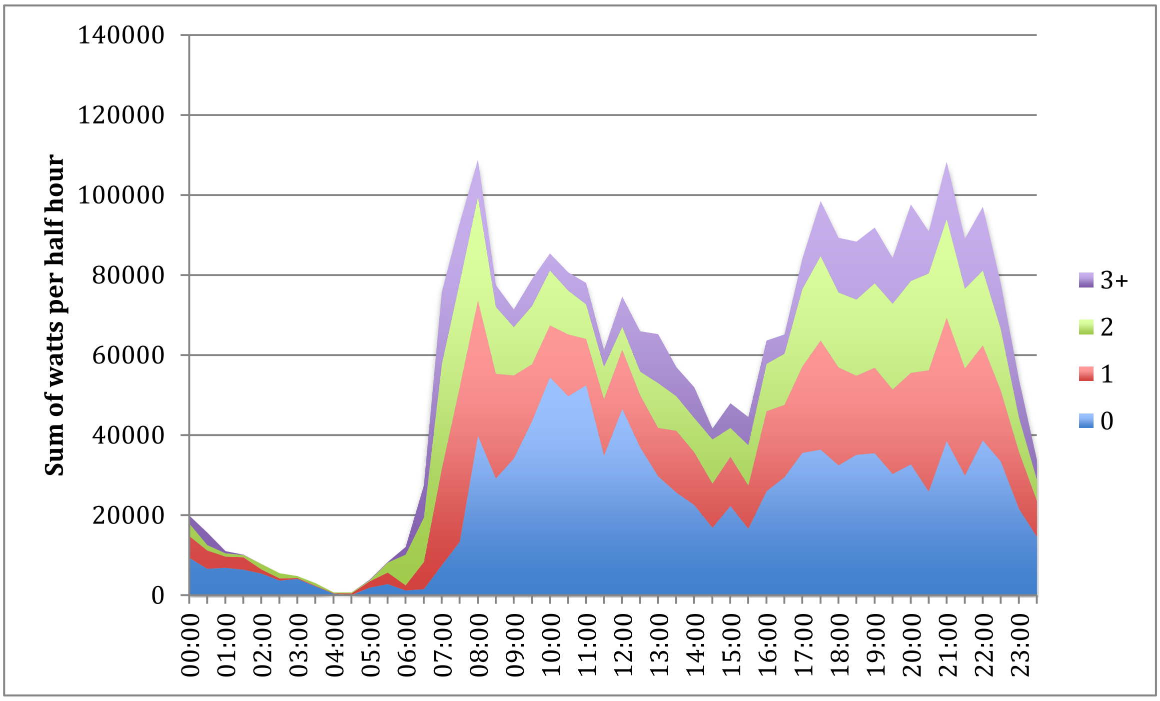

Figure 10: Model 1 imputed total half-hourly household electricity demand by number of earners for LSOA E01017139 (Source: Author's calculations using Census 2001 & UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

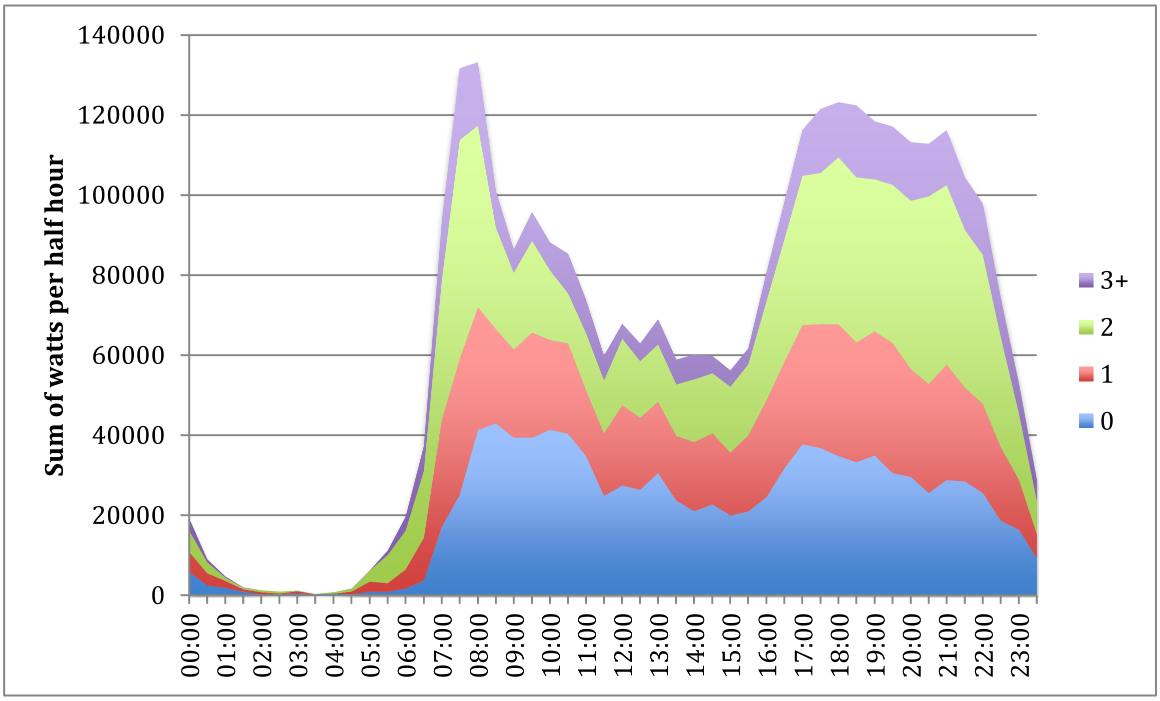

Figure 11: Model 1 imputed total half-hourly household electricity demand by number of earners for LSOA E01017180 (Source: Author's calculations using Census 2001 & UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

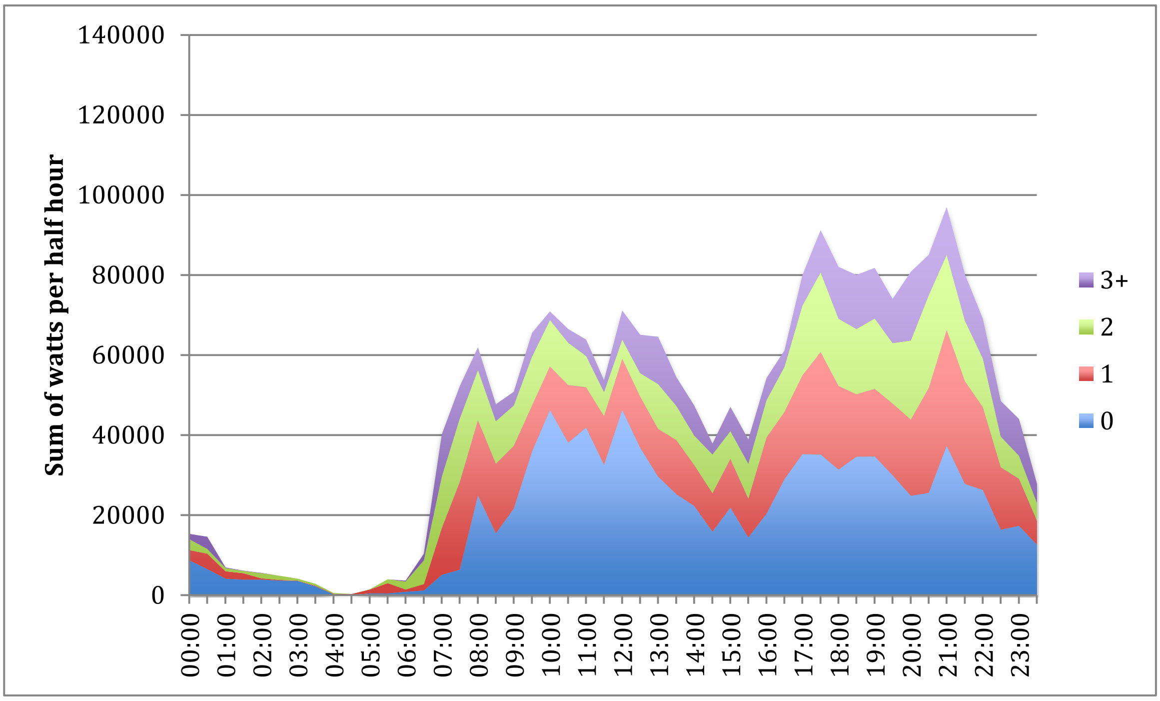

Figure 12: Model 2 imputed total half-hourly household electricity demand by number of earners for LSOA E01017139 (Source: Author's calculations using Census 2001 & UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

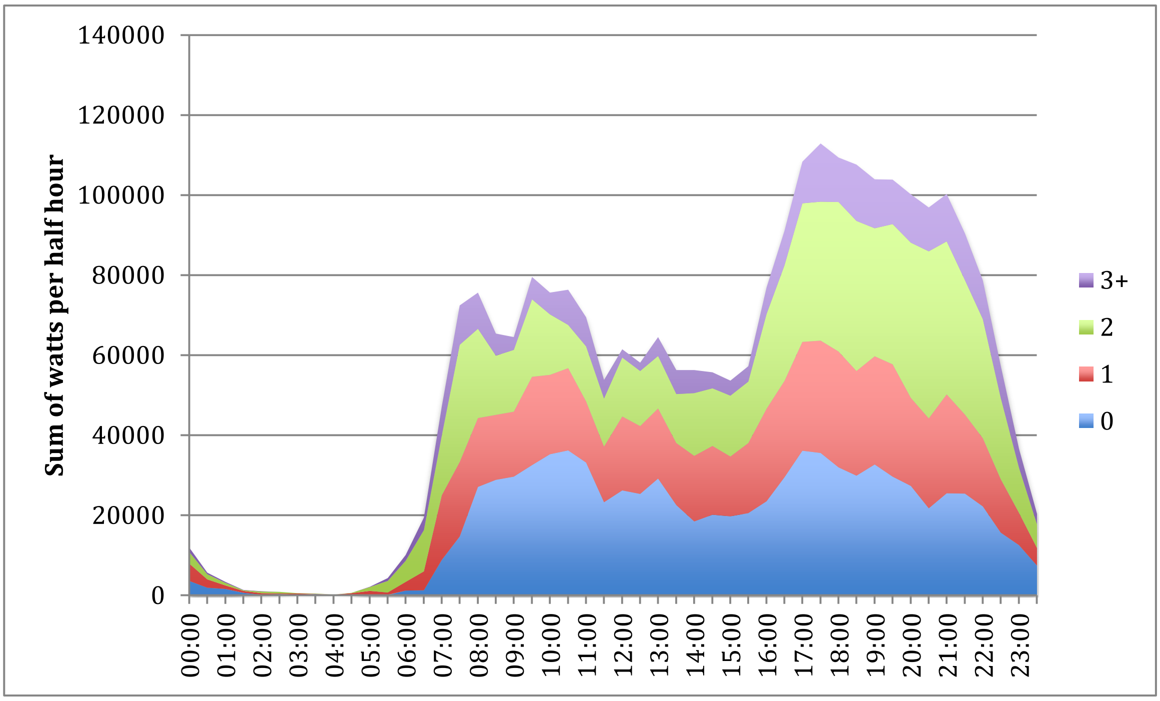

Figure 13: Model 2 imputed total half-hourly household electricity demand by number of earners for LSOA E01017180 (Source: Author's calculations using Census 2001 & UK Time Use Survey 2000/1, weekdays, November 2000 - February 2001, weighted)

The different levels of contributions each make to the overall demand profiles reflect the different proportions of households with 0,1,2 or 3+ earners in each LSOA. In addition the differing reported activity profiles, combined with the Model 1 assumptions produce distinctly different overall demand profiles for each small area with a an accentuated morning peak and higher overall evening demand in E01017180.

Figure 12 and Figure 13 on the other hand show the same profiles for the same small areas but under the less electricity intensive 'washing/dressing self' power demand assumptions implemented in Model 2 (see Table 2). As we might expect the model suggests the most notable reduction will be seen in the area with the highest proportion of earners and especially so in the early morning.

Whilst the detailed differences between the profiles are clearly driven by the assumptions in the electricity demand imputation method, they are also driven by the different composition of each small area (LSOA) and the energy-using activities recorded in the time-use diaries of the household occupants. In presenting the analysis according to the number of earners we have drawn attention to both of these kinds of differences but without claiming that the number of earners in a household is necessarily a driver of temporal electricity demand as there are likely to be many other factors in play which combine to produce the profiles we have chosen to summaries in this way. We could, equally, have presented the results according to the number of children in households in each area, by household composition or by age group.

The results therefore make clear the value of the approach in enabling not only overall consumption to be assessed for a given small area but also an assessment of the relative contribution of different kinds of households. This will enable an assessment of the potential change in area level consumption due to interventions that are aimed at or work best for particular households – a key aim of the SAVE Customer Model.

9 Summary

This report has laid out the requirements for the SAVE Customer Modelling Framework and has described the approaches that will be used in its implementation.

Overall the approach is based on the microsimulation of demand at the 10-15 minute time period, per day per household level although results are likely to be aggregated to half hours for reporting and presentation purposes. All modelling, including scenario models will be implemented at this level and will only be aggregated to 'average' profiles for different household types or groups for presentation purposes and, if appropriate, as input to the SAVE Network Model. Where feasible the model will include insights from the community coaching trials.

The household level microsimulation will be combined with Census 2011 data to produce small area (Census LSOA) estimates of baseline and intervention scenario temporal demand profiles. Where possible, these results will be validated against data collected though substation monitoring conducted by the community coaching trials.

The first iteration of the Customer Modelling Framework will be established using the baseline SAVE household trial data by December 2016. The second iteration, incorporating the results of the SAVE household intervention trials and defined behavioural scenarios will be completed by June 2018.

The model itself will be implemented as a set of open statistical scripts which will be made available for re-use beyond the life of the project alongside the planned submission of the anonymised SAVE trial data to the UK Data Service.

For wider dissemination aimed at non-expert audiences, selected results and tables, including a high level query engine will be made available through a web-based user interface which will include map-based visualisations of the small area results.

10 Acknowledgements

The United Kingdom Time Use Survey, 2000 was collected by Ipsos-RSL and the Office for National Statistics with sponsorship from the Office for National Statistics, Department for Culture, Media and Sport, Department for Education and Skills, Department of Health, Department for Transport, Local Government and the Regions and the Economic and Social Research Council. It is Crown Copyright and is distributed by the UK Data Archive, University of Essex, Colchester.

Census 2001 data were created and funded by the Office for National Statistics and distributed by the Census Dissemination Unit, MIMAS (University of Manchester). This information is licensed under the terms of the Open Government Licence [http://www.nationalarchives.gov.uk/doc/open-government-licence/version/2].

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