Exploring socioeconomic and temporal characteristics of British and German residential energy demand

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Abstract – The British and German residential sectors account for similar fractions of national energy demand and carbon emissions. They also exhibit underlying differences in the building stock, fuel split, tenure and household load profiles. The temporal habits in British and German households are also quite different, which is challenging to measure due to the paucity of German smart meter data. This contribution takes this background as a starting point to explore some of the temporal and socioeconomic characteristics of residential energy demand in Britain and Germany. The Centre for Renewable Energy Systems Technology (CREST) residential load profile generator is updated for the UK and extended to the German context and validated with standard load profiles, providing high levels of accuracy according standard normalized root-mean-squared error (NRMSE) measures. The paper then analyzes the energy-related activities of different socioeconomic household groups based on with National Time Use Survey data from both countries. The analysis showed some clear differences between groups and countries, which are a reminder of the importance of non-energy policy (e.g. school hours) in determining peaks. As well as encountering useful insights into international differences in energy-related behaviour, the results showed some key differences within specific socioeconomic groups, such as single persons, families with children, and pensioners. Further work will focus on extending the German CREST model to include a German appliance stock, as well as allocating these appliances according to households' socioeconomic characteristics. The definition of the groups themselves needs to be refined, perhaps to include multiple variables and based on clustering or similar techniques, and validation with smart meter data.

KEY WORD SET: TIME USE DATA, RESIDENTIAL SECTOR, LOAD PROFILES, ENERGY DEMAND

I. INTRODUCTION AND OVERVIEW

The energy transition towards a low carbon energy system involves rapid developments of renewable electricity generation capacities and a widespread realization of energy efficiency potentials. Both of these measures increase the importance of the conventional demand side, which is defined here as those end-use sectors that solely demand (and do not generate) electricity. Especially households and residential buildings are relevant in this context because buildings account for about 40% and 36% of the total European end energy consumption and greenhouse gas (GHG) emissions respectively (De Groote and Rapf 2015).

These measures will also be increasingly important in the context of the discussion around flexibility in the energy system, and the role of the residential sector in delivering this. This work opens up an avenue for further work in the area of flexibility, by highlighting differences in terms of 'baseline' in different soci-oeconomic household groups and different countries. The motivation for examining two countries, namely Germany and the UK, within this case study, stems from the fact that these are the two largest residential electricity markets in Europe, hence with the highest aggregate economic potential for flexibility.

In addition to the overall demand, the temporal profiles of electricity consumption are important be-cause they dictate, to large degree, which measures are required to integrate increasing amounts of inflexible electricity supply from renewables. The temporal power demand of households is captured on an aggregate

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level by standardized load profiles. Network operators have developed these profiles to forecast power demand for large groups of customers. An example of these normalized curves for the UK and Germany, in a weekday during the transition period, is shown in Figure 1. Whilst the curves have a similar overall shape, there a differences in the timing and duration of the peaks, such as a much more pronounced lunchtime peak in Germany, and a longer evening peak in the UK.

As shown in section II, significant attention has been paid in the literature to the implications of different socioeconomic variables on households' overall energy and power demand. Despite reaching some strong overall conclusions about the variables that influence demand, these studies do not agree on the extent to which these variables do so, and the variables together often only explain about 50% of the variation in demand. One reason for this lack of explanatory power might be the lack of attention to peoples' activities, which determine the timing of residential electricity demand. Research that examines activities in relation to electrical demand profiles has the potential to overcome this problem.

One the other hand, time-use data has frequently been employed to develop stochastic simulation models of residential energy demand. Based on diary entries from a representative sample of the national population, these models simulate occupancy and activity probabilities to impute power demand. Examples that are based on first order Markov chains include the open source UK CREST model, originally developed by Richardson et al. (2008, 2010) and later independently further developed to include space heating and hot water by McKenna, E. et al. (2016) and McKenna R. et al. (2018), and the model for Sweden presented by Widén & Wäckelgård (2010). Fischer et al (2015) do not use Markov chains, but derive probabilities for daily starts, start time and duration for nine activities from time use data for the German Synpro model. These models are typically effective at producing aggregated average (mean or median) profiles for several hundred households that show an adequate agreement with the standardized profiles, as shown exemplarily in Figure 1. However, their ability to generate reliable profiles for individual socioeconomic groups has not yet been thoroughly analysed. As shown in section II studies have not (yet) typically employed time use data alongside load profiles. Alongside an increasing availability of smart-meter data for thousands of households, these models provide the background and starting point for the present contribution. Hence the objectives of this paper can be formulated as follows:

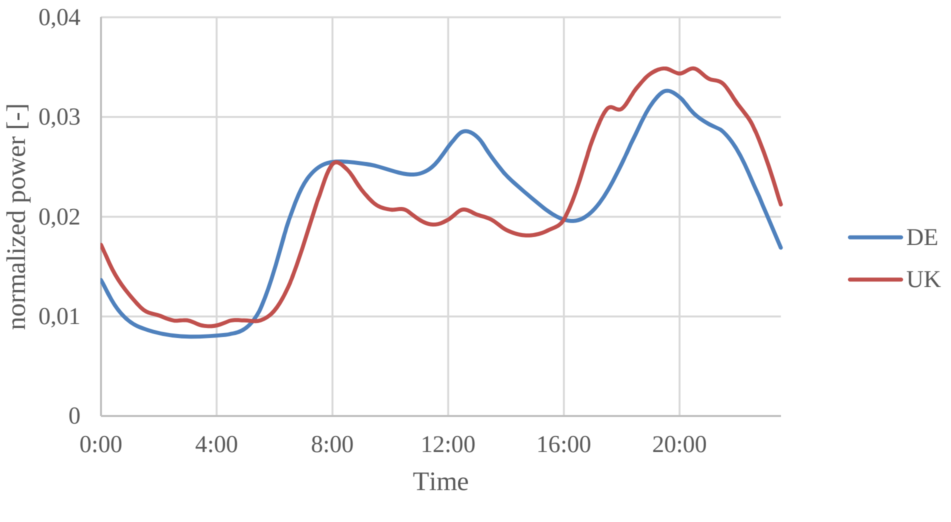

Figure 1: Comparison of normalised (total sums to unity) standard load profiles for German (VDEW 1999) and the UK (Elexon 1997) for a weekday during the transition period

1. To update the CREST model for the UK and extend it to the German context, and validate with standard load profiles
2. To analyze the energy-related behaviour of different socioeconomic household groups:
    a. At the activity level with Time-Use-Survey
    b. At the load profile level with the CREST model and based on metered load profiles

The remainder of the paper is structured as follows. Section II provides a literature review and derives the moat significant socioeconomic variables, which are employed in the remainder of the work. Section III then presents the methodology, including the simulation of residential electricity demand with time use data and the analysis of empirical (smart meter) data. Section IV then presents and discusses the results, before section V closes with conclusions and an outlook.

II. LITERATURE REVIEW

Several studies have analysed the socioeconomic influencing factors on households' overall energy demand, as well as their electrical load profiles (for a discussion, cf. for example McKenna, R. et al. 2016). The aim of this section is to review literature on the relationship between household composition and residential electricity demand in different types of study, especially time use research and time use studies connecting with actual metered electricity data.

II.1 Time-use data for residential electricity demand modelling

There is a growing literature on time use data and how this can inform load profiles and peak demand. Existing studies on time use and energy consumption tend to be based either on synthetic stochastic models or measured time use survey data. Studies based on time use data consist of a growing body of work which typically relies on national time use surveys to either model electricity load profiles or infer energy related proxies, such as occupancy.

Early work comprises a study by Capasso et al. (1994), who modelled 15-minute period consumption patterns based on appliance and homeowner variables; Wood and Newborough (2003), who used three characteristic groups to explain electricity consumption patterns in the household: "predictable", "moderately predictable" and "unpredictable"; Stokes et al (2004), who modelled domestic lighting with a stochastic approach, generating load profiles with a resolution of 1 minute from the 30 minute resolution of measured data in 100 households; and a study by Firth et al. (2008) who analysed groups of electrical appliances (continuous and standby, cold appliances and active appliances) in terms of time of the day when they are likely to be switched on.

More recent studies have employed similar approaches to several European countries. For example, for the UK Richardson et al. (2008) make use of the National Time Use Survey to develop an occupancy model for UK households, later developed into an electricity demand simulation model by Richardson et al. (2010). In a similar UK study, Blight et al. (2013), examined the occupant behaviour and its impacts on heating consumption in Passivhaus buildings. Using Richardson et al. (2008) model the authors developed occupancy, appliance-use and door-opening profiles. Their finding suggests that the occupancy patterns are less significant factors to the total heating energy than other like set point temperature and appliance use. In Sweden, Widén et al. (2010) developed a model simulating household activities based on time use data. The timing of electricity demand is derived from time use data combined with appliance holdings, ratings and daylight distribution. The same author applied the same model to water heating (Widén et al, 2009a) and lighting (Widén et al, 2009b). In Ireland, Duffy et al. (2010) applied the same probabilistic modelling to five different dwelling types. They compare the synthetic data generated by the model with metered electricity demand. Their findings show unusual peak loads during the day and night which do not correspond to existing load profiles. In Spain, López-Rodríguez et al. (2013) used the National Time Use Surveys to generate activity specific energy consumption profiles or to cluster consumers based on their states of occupancy active or inactive. They used the generated profiles to identify appliances that were running during the occupancy. In Germany, Fischer et al. (2015) use the presented Time Use Survey based approaches and further develop them by considering household specific sociodemographic behavioural differences, three different type days (weekday, Saturday, Sunday), relationships between duration and start time of activities and seasonal usage patterns. The stochastic model enables the simulation of high resolution electric load profiles. However, socio-demographic differences in the load profiles are not discussed in detail. Additionally, Aerts et al. (2014) using the Belgian time of use data define a three-state probabilistic (e.g. defining inactivity state as home and awake) model to generate occupancy patterns. The strength of this model is in combining socio-economic aspects of population with occupancy data in investigating the clustering of different occupancy patterns.

Others, also consider socio-economic characteristics (such as age, employment status, income or main activity) to be powerful predictors of occupancy characteristics. For example, Dar et al. (2015) using the Norwegian time-of-use survey investigated the effect of occupant behaviour and family size on the energy demand of a building and the performance of the heating systems. They identify nine occupancy categories based on number of occupants and working hours. The limitation of this study is in the way modelling was done, including only household parameters that define either a Low Energy House or Passivhaus, and excluding poor thermal performing houses.

II.2 Socio-demographic shaping of residential activities and energy demand

In general there is evidence that the overall energy demand of a household is closely correlated with its income, although other factors also play a significant role (e.g. Jones et al. 2015; for a spatial analysis for the UK see Druckman & Jackson 2008). Haldi & Robinson (2011) suggest that behavioural factors alone can account for a doubling of building energy demand and the diversity between occupants may have an even stronger effect. In the context of low-energy dwellings Gill et al. (2010) find that occupants behaviour account for the 51%, 37%, and 11% respectively of the variance in heat, electricity and water consumption. Despite these findings, some studies that have attempted to explain the variance in internal temperatures (Kelly et al. 2013) and energy demand (Hübner et al. 2015) have been unable to fully do so. Whilst Kelly et al. (2013) are able to explain 45% of the variation in internal temperatures using panel methods, Hübner et al. (2015) are only able to account for 44% of variability in residential energy consumption.

Comparative time use research has also focused on how activities are carried out differently by different socio-demographic groups in various countries. In this case the research focus is on the performances of individuals and their practices that relate to energy consumption. Rather than clustering and segmenting based on socio-demographics, clustering by activities allows the identification of different patterns of domestic activities that are not well defined by demographics. The Sustainable Practice Research Group (Pullinger et al. 2013) carried out an analysis of UK laundering practices aiming to identify socio-demographic variables which are correlated to clusters of laundering practices. Six clusters of laundering practices were identified, with the most common being a laundering practice performed in a washing machine that is loaded to its full capacity and with the settings that are never changed (Pullinger et al. 2013). While the researchers argued that household socio-demographics are poor predictor of cluster memberships, they argue that the socio-demographic characteristics such as age, could help in understanding the performances of practices over time or with disappearance of specific activities. Similarly, Anderson (2017) using time-use diary data explored the temporal change in laundry practices in the United Kingdom over the last 20 years. While the research suggests statistical relationship between employment status and weekday morning and weekday evening laundry, he argues that social-demographic are week predictors of laundry practices.

III. DATA & METHODOLOGY

This section presents the data sources employed in section II.1 followed by the methodology in section II.2. At the heart of the approach which places social practices at the centre of our understanding of the dynamics of energy demand is the position that the timing of energy demand is determined by the way practices are ordered in time Torriti (2017). In this paper we therefore consider energy to be part of the practices that we investigate (Shove et al. 2014). According to this conceptualization people do not ‘demand ‘energy for its own sake, but as part of the routine accomplishment of everyday practices, such as cooking, watching TV or commuting to work (Shove et al. 2014).

III.1 Selection and availability of socioeconomic variables

Summarizing from the preceding section II and comparing the availability of data with the desired variables leads us to the overview shown in Table 1 below, whereby we focus on family structure (includes age and number of children), income, household size, property type, and tenure. The following section explains the methodology employed to analyze this data.

Table 1: Metadata availability, from TUS and metered data

Variable	Low Carbon London	German Meter Data	In UKTUS data?	In DETUS Data?
Source	**Schofield et al. 2015**	**Hoffmann et al. 2012**	**CFTUS (2016)**	**Statistisches Bundesamt (2015)**
No of people	No of people	No of people	Adults, children, total in household.	No of people and children under 18
Employment	Work from home (yes/no)?	Employed and type of job	11 cats. including self-employed, retired, mat. leave, unemployed, study, homestay and unemployed.	6 cats including pensioner, no. of employed people
Household structure	Very many categories	7 categories	8 cats: single, married, w w/o kids, ”unclassified“ + “other”	5 cats: single, pair no kids, single parent w/kids, pair w/kids, other
Age	For each individual	No in bands: 0-5, 6-17, 18	For each individual and in bands: 0-14, 0-16, 11-15, 16-19, 5-10.	Exact age in years, then 80-84, 85+
Type of building	Detached, semi, terrace (2), flat	1-2 family, multi-family house	House/bungalow, flat, rooms, other,	Only floor area and no. of rooms
Electric heating	Yes/no	Yes/no	No information	No info
Rents/owns	Yes/no	Yes/no	Owns, Mortgage, Part rent, Private rent, social housing, rent free.	Rents/owns/free living
Income	Missing	8 bands	Individual + 13 bands	Monthly income in 18 bands
Appliances	No of each appliance	Not present	No of each appliance	Computer number, car number, internet access y/n
Sex	No of people m/f	Not available	Each person	Each person

III.2 Methodological approach

The overall approach developed in this contribution consists of a combination of theoretical and empirical approaches. On the one hand, we employ time use data for the UK (UKTUS) and Germany (DETUS) to analyse different households' activities throughout the day. In a second step we develop a simulation model to generate residential electrical load profiles for these household groups, based on this time-use data. In a third step, we analyze metered consumption data, in order to both validate the developed models and derive insights into the demand profiles of these socioeconomic groups. Therefore we aim with this interdisciplinary investigation to narrow the gap between social science and engineering models in understanding energy demand. This overall approach is illustrated in Figure 2. Note that the validation with smart meter data is still oustanding and is therefore not part of this paper.

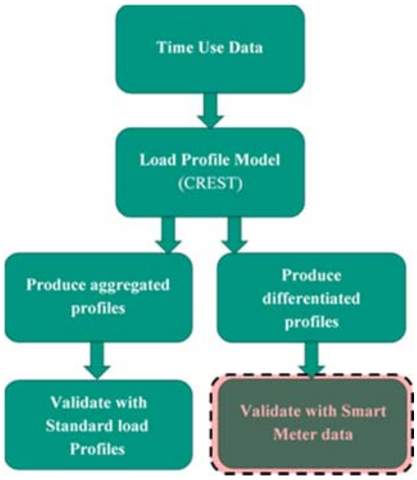

Figure 2: Visual presentation of the overall approach

The method of extracting occupancy and activity profiles from TUS data has been widely employed previously (e.g. Richardson et al. (2008, 2010) and Widén & Wäckelgård (2010). Survey participants complete several diary days at high temporal resolution, for which they specify their main activity and one or more parallel activities, as well as (in some cases) their location. Through the combination of several days' diaries from all survey participants and the application of weighting factors (see Table 3 below), it is possible to generate 'average' occupancy activity profiles for the whole population. In this case we employ a four state occupancy model (McKenna et al 2015), thereby differentiating between four states, combinatorially derived from at home (or not) and active (or not), as shown in Figure 3 below. The state 'at home, inactive' essentially relates to the relevant occupant being asleep; apart from the base load (e.g. for refrigerators, standby etc.) energy-related activities only occur in the state 'at home, active'. Each occupant in the household is allocated an occupancy matrix as illustrated in Figure 3, with the left side showing the four states, and the right hand side showing an example of transition probabilities (transition probability matrix, TPM) – in this case for a single person household in both cases, hence why the two digits are either 0 or 1.

Code of occupancy	Activity state
00	Not at home, not active
01	Not at home, active
10	At home, not active
11	At home, active

Combined State @13:00	Combined State @13:10			
	00	**01**	**10**	**11**
00	0.7965	0	0.0338	0.1697
01	0	0	0	0
10	0.06	0	0.495	0.4451
11	0.2432	0	0.0532	0.7036

Figure 3: Method of deriving occupancy / activity profile from TUS data

Having derived the TPMs, the next step is to determine activity profiles, which are the central mechanism through which individual activities are grouped and allocated to electrical appliances (cf. Figure 4 below). The original CREST model has six activity profiles (plus one 'other'), which are adopted in the present work. The individual activities within the TUS datasets are thus manually allocated to these six categories, following the method of Richardson et al. (2010). For the German TUS data, the process involves somewhat more expert judgement, due to the fact that the activity codes are different. Finally, two additional input datasets are required for the CREST model, namely the 'starting states' and the '24-hour occupancy probabilities'.

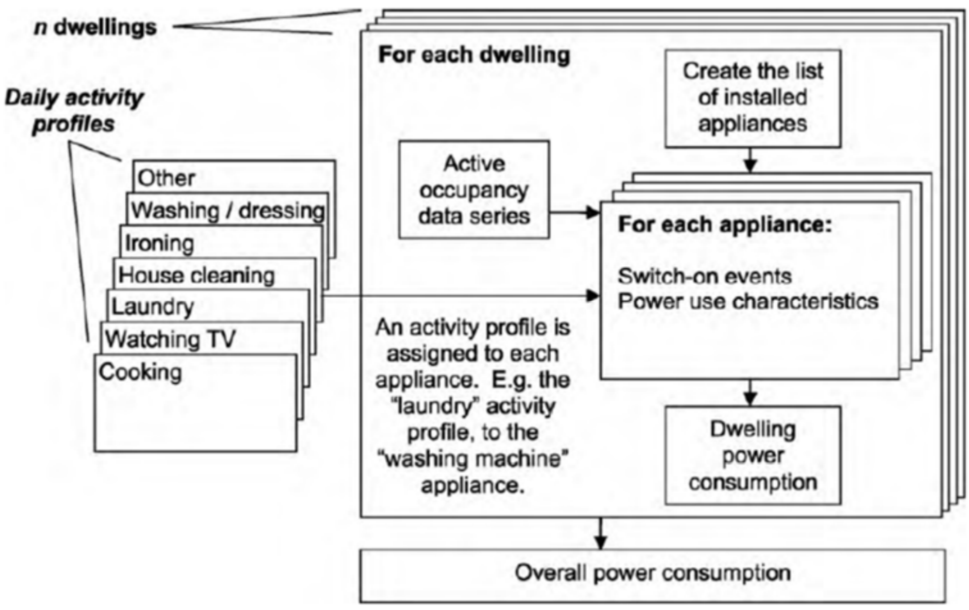

Figure 4: Electricity demand model architecture (Source: Richardson et al. 2010)

The above description applies to the unmodified version of the CREST model, which only differentiates between the number of people in the household. In the context of the present work, further differentiations were made according to the variables outlines in section III.1 above. The final stage in the methodology involves deriving the electrical load profiles for the same socioeconomic groups from metered data. In the context of this work, the original intention was to do this for both Germany and the UK. But in the process of analyzing the German smart meter data from the Modern Energy Saving Systems in Households project (Hoffman et al. 2012), it was found that the data contains many errors and extreme values. This explains why the HfT in Berlin (Tjaden et al. 2015) only employed 70 of the total around 500 households in their analysis based on this data. For this reason, the German data is not used in this contribution and instead only the Low Carbon London dataset is employed for the UK (Schofield et al. 2015). This dataset contains measured load profiles for over a year for around 5000 households within the distribution networks of UK Power Networks, as well as some rich metadata on these households as illustrated in Table 1 above.

IV. RESULTS AND DISCUSSION

This section presents the results of the study, as follows: the first section discusses the lessons learned in working with two TUS datasets; the second section then validates the generated load profiles for the UK and Germany with the standard load profiles; the third section compares socioeconomic groups in terms of their activities; and the fourth section discusses these results, their wider implications and the method in general.

IV.1 Lessons learned from employing two TUS datasets

Table 3 below summarizes the main differences between the two employed datasets, namely the UKTUS 2014/2015 and the DETUS 2012/2013. Whilst the two datasets are broadly similar, there are some key structural differences that make an international comparison of this type challenging. For example, both datasets cover around 10-11,000 individuals and 5000 households, whereby differences are mainly due to the size of the sampled populations. However, the number of diary days differs significantly: in UKTUS only 1.5 days are entered on average per participant, whereas in DETUS this average is 3. Another difference relates to the number of parallel activities: whilst this is 4 in UKTUS, it is only 2 in DETUS. The location of the activity is also specified in every time period of UKTUS, whereas in DETUS it is only explicitly stated for the first and last periods of the day. In addition, for UKTUS the location of the household is given at the county level, whereas for DETUS there is only a differentiation between east and west Germany. Finally, there are some differences in the weighting factors available, and the UKTUS clearly has more of these (the employed factors are bold in Table 3).

Table 2:Lessons learned with comparing UK and German TUS datasets

	UKTUS	DETUS
Individuals	10208	11000
Households	4741	5000
Diary days	16550	33000
Parallel activities	Up to 4	Up to 2
Location of activity	Given	Given at start and end of day, otherwise implied
Location of household	County	Only East/West split
Weighting factors	Household, individual, **diary** (day and individual), 7 day week	Household, individual, **diary**
Allocation of activities to 6 CREST categories	Manual based on original allocation from Richardson et al. (2010) and expert judgement	

IV.2 Comparing synthetic and standard load profiles for the whole population

The results of the generated synthetic load profiles (i.e. with the CREST model) compared to the standard load profiles (SLP) for the UK and Germany are shown for a weekday (WD) in summer and winter in Figure 5. Overall there is a good agreement between the synthetic and standard load profiles, with low values of the Normalized Root Mean Squared Error (NRMSE)[2]. It should also be noted that behavioral seasonal effects in the time use data are not taken into account. However, seasonal effects in the lighting are taken into account since they are derived from the irradiation conditions. Also, the summer evening peaks are not well captured in CREST model for the UK, as the standard load profile in this case appears to have a flatter, extended peak than the model reproduces. Overall, though, the CREST models generate aggregated load profiles that have only very small deviations from the respective standard load profiles.

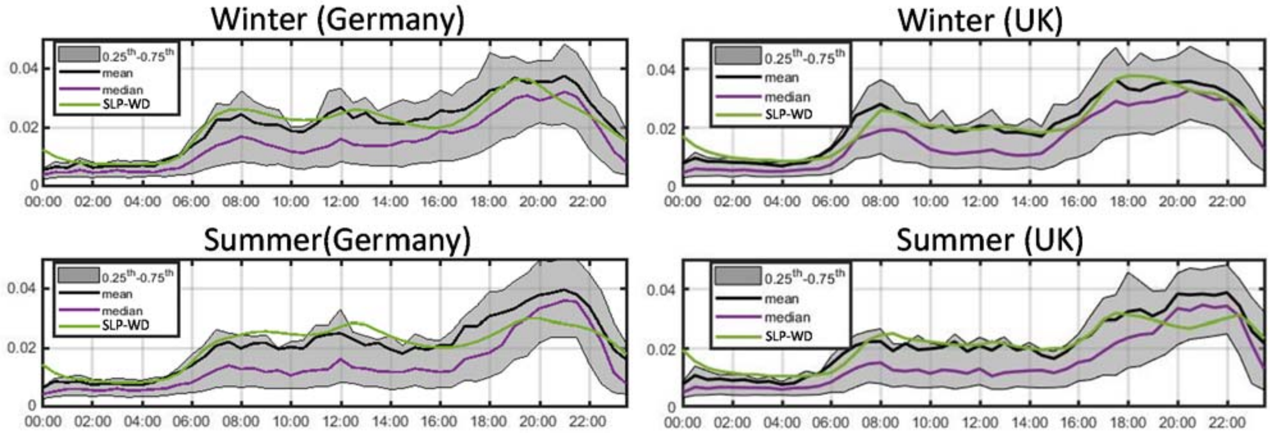

Figure 5: Synthetic vs. standard load profiles (SLP) for whole population in Germany and the UK, in summer and winter

IV.3 Comparing activities between Germany and the UK

Figure 8 below shows a comparison between activity probability distributions in Germany (left) and the UK (right), for the whole population and all diary days. Shown is the probability, at a given time of day, that one or more of the occupants in the household are carrying out one of the six specified activities. Whilst both of the curves have similar overall shapes, there are some interesting differences between them. Firstly, the morning peak is a lot more pronounced in the UK, especially due to wash/dress and cooking activities. Whereas in the UK the overall activity intensity steadily decreases until the early evening, the second key difference is that in Germany the midday peak is much more pronounced. This seems to be almost exclusively due to the more intensive cooking activities at lunchtime in Germany, compared to the UK. The third main difference lies in the evening peak, which is shorter and higher in Germany than in the UK. Whilst there are clearly a number of possible explanations for these differences, they certainly indicate some fundamental differences in households' habits between the two countries. The breakfast time difference might be related to a more traditional English cooked breakfast compared to 'continental style' cold food, with a German tendency to cook more at lunchtime compared to British 'working lunches' with sandwiches and convenience food. The differences in the evening peak might relate to different working hours, a higher tendency to cook evening meals in the UK, and a higher intensity of TV watching amongst German households. Whilst the causes for the different activities are uncertain, they would at least partly seem to explain some of the differences between the standard load profiles in Figure 1.

The plots in Figure 9 below compare the activity probability distributions for different family structures in Germany and the UK. These plots were generated, as outlined in section III.2, by interrogating the time use datasets for the respective socioeconomic group and producing activity probability distributions in the same way as for the whole population. The plots reveal quite strong similarities in evening habits, apparently related to TV watching. The shape of the peak for TV watching in Germany is later and shorter for households with

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[2] Winter DE: NRMSE H0/mean 0.0999, Summer DE: NRMSE H0/mean 0.1365, Winter UK: NRMSE H0/mean 0.0948, Summer UK: NRMSE H0/mean 0.1395

children, as well as more intensive for single households, which might partly explain the observations for the whole population noted above.

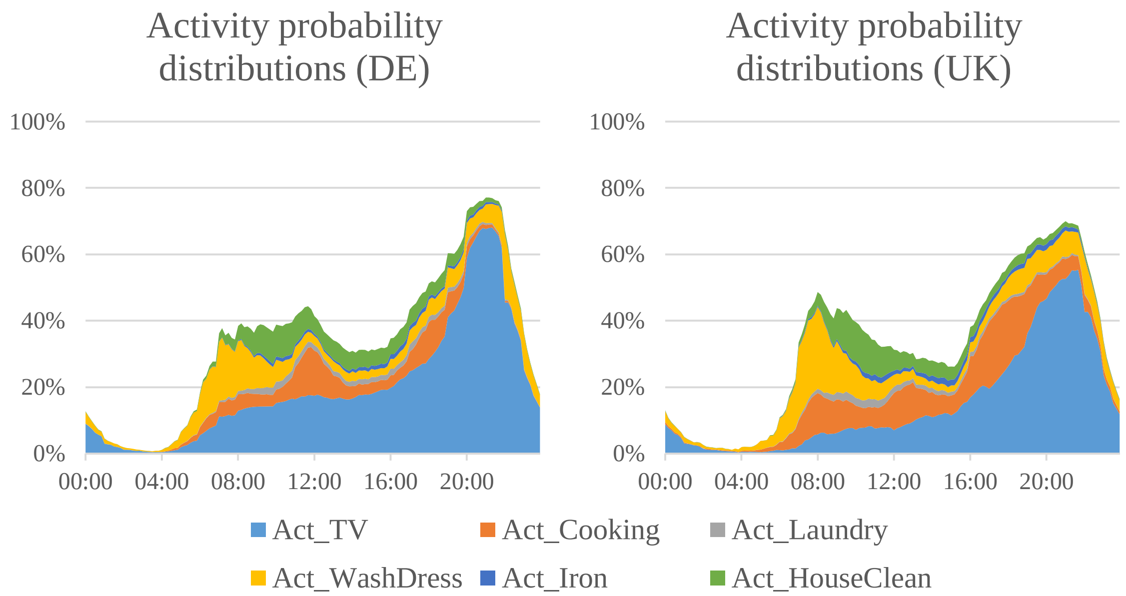

Figure 6: Probability of >=1 active person undertaking one of these six activities

In general, it seems that the effect of children is more pronounced in Germany than the UK, leading to a higher morning peak. In both countries, young people and couples tend to have a broader evening peak, suggestion less homogenous behaviour patterns in these age groups. Also, although not shown here, the analysis revealed that the evening peaks in the UK are broader and gender- and children-related, as the female occupancy increases significantly after 4 pm.

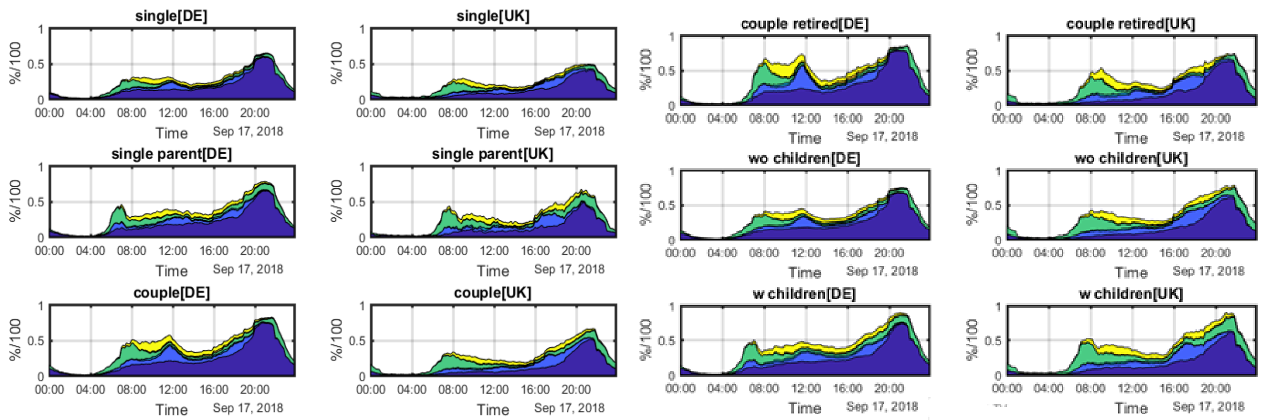

Figure 7: Comparison of activity probability distributions for different family structures in DE and UK (for legend see Figure 10)

The plots in Figure 10 compare the same activity probability distributions for different household sizes in Germany and the UK. As expected and confirmed with empirical data, the size of the morning peak increases with the number of residents. For the UK, the number of occupants also has a strong effect on the size and shape of the evening peak, which is less the case for Germany. The midday peak already noticed in Figure 8 only becomes pronounced above two household occupants, yet for three and four people it is less evident and only becomes significant again at five household members. Comparing with Figure 9 indicates that this lunchtime peak is especially caused by retired couples in Germany; presumably, larger German households also have a higher probability to cook at lunchtime. In addition, despite not being shown in any of these figures, the analysis revealed only minor differences between the profiles of households at different income levels. This would seem to suggest that appliances/ownership are perhaps more important in driving higher overall energy demand for higher income groups than activities per se. Again, whilst these plots do not explain the reasons for the different activities, they do at least provide some insights into the ways in which energy-related activities differ between household types.

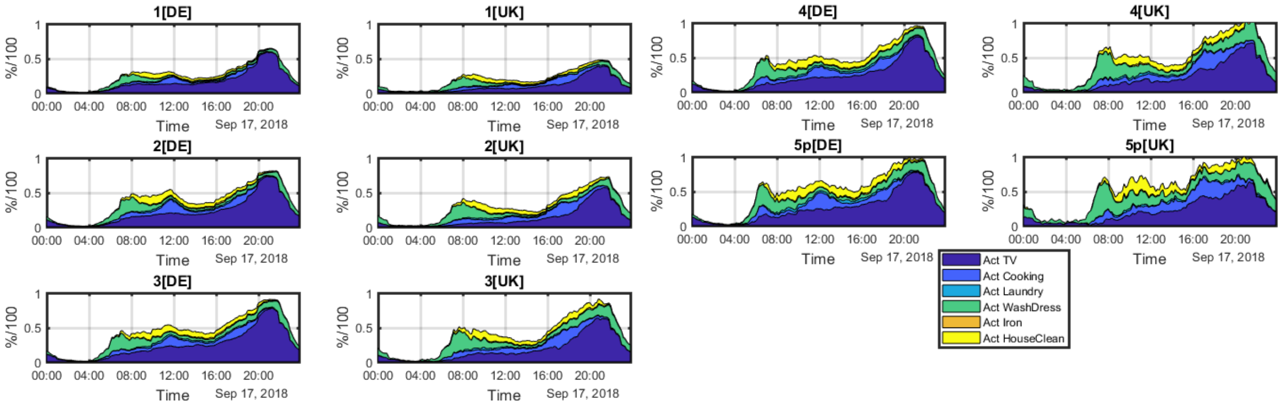

Figure 8: Comparison of activity probability distributions for different HH sizes in DE and UK (note that the more 'peaky' profiles with 5+ occupants due to small sample sizes)

IV.4 Discussion

This section briefly discusses the results, some of their wider implications and critically assesses the methodology. Overall, the results confirm/validate the assumed standard load profiles for Germany and the UK for the whole population. But more interestingly they also shed light on some of the differences in residential behaviour between these two countries, especially for specific sociodemographic groups. These insights could be relevant to wider questions and research around flexibility in the energy system, for example, which many studies have shown to have significant economic potential. Flexibility is also associated with costs, which ultimately have to be paid by households. In order to understand which loads contribute to flexibility, our analysis divides residential demand by activity. This enormous potential might attract the interest of a variety of investors including those that currently do not operate in the energy sector. One of the decisions investors will need to make is whether and to which extent to invest in Germany and the UK. Whilst this paper does not provide a direct measurement of the flexibility potential, it points to differences in the composition of household electricity demand and peaks in Germany and UK as a starting point for evaluations of flexibility market potential in these two countries. In relation to costs, these are likely to differ across socio-economic categories of users. For this reason, a segmentation based on standard socio-economic parameters provides insight as to the composition of activities at peak demand.

The method can be assessed along two main strands, relating to Time Use Data and the CREST modelling approach respectively. Firstly, the time use data in itself presented several challenges in terms of consistency in approach and assumptions (cf. Table 3). So a certain degree of expert judgement was required, especially relating to the allocation of (German) activities to the CREST activity types, when imputing the location of (German) activities, as well as when dealing with parallel activities. The questionable accuracy of the CREST Model in capturing these parallel activities has been raised elsewhere (McKenna et al. 2017), but there remains a more general question about the reliability of time-use data for parallel activities. It seems plausible that the prevalence of ICT devices makes parallel activities increasingly common, but that these are not well recorded in TUS data. In addition, there is the risk of encountering insufficient sample sizes when differentiating according to many variables, which can also be seen in some of the results (cf. Figure 10, for 5+ occupants) and weakens their statistical strength. Whilst it would be desirable to also further develop this method to consider location-specific household profiles, the lack of spatial resolution on the German side is a clear challenge.

The method employed in this paper has demonstrated that the application of the CREST model to another national context, in this case Germany, is in principal possible. But there remain some research challenges before this task can be considered complete. Firstly, there are some fundamental weaknesses in the CREST model, which have not been addressed here but should be in further work attempting to improve such approaches, for example the lack of seasonal behaviour differentiation and unrealistic nightime/baseline demand profiles (see discussion by McKenna et al. 2017). More specifically related to the approach applied here is the issue of allocating activities to activity groups, in this case based on the six (plus ‘other’) activity profiles originally implemented in CREST. These activity types are certainly adequate for representing the whole population, only differentiated by number of occupants. But the attempts to produce profiles for different household types in this paper have shown that these activity types do not perform well. This problem is almost certainly also related to the fact that the appliance stock and household allocation in the German CREST model was not updated. In practice, not only should the appliance stock be updated to reflect the German stock, it should also consider differences between socioeconomic household groups. A different, more detailed categorization of activities might also enable a consideration of flexible appliances and thus the fraction of the load profile that can be considered flexible. Such an approach is employed by Fischer et al. (2015) in Synpro, but there are some unanswered questions around the validity of the resulting profiles, which the authors claim to have validated with data from the Intellikon project (430 datasets with sd differentiation), cf. Fraunhofer ISE (2011). The link between the activities and the appliances is much more detailed in Synpro than it is in CREST. Synpro uses appliance loadprofiles, sd-group specific appliances and a correlation between starting time and duration. Further work should therefore attempt to improve the link between the activities and the appliances for the UKTUS data and to compare the results with LCL dataset. This was originally planned for this study (cf. Figure 1) but the method for characterising socioeconomic still requires some refinement.

V. CONCLUSIONS & OUTLOOK

Against the background of an increasing importance of the residential demand side, this paper set out to address two main objectives. The first one, i.e. to update the CREST model for the UK and extend it to the German context, and validate with standard load profiles, has been at least partly achieved. The extension was hitherto limited to the time-use data; further work should also update the appliance stock, as analyses of different socioeconomic groups suggested this to be significant. Nevertheless, the UK and German CREST version is able to reproduce the standard load profiles with a reasonable degree of accuracy, similar to that for the UK model, but both seem less reliable for certain socioeconomic groups.

The second objective was to analyze the energy-related behaviour of different socioeconomic household groups, on the one hand at the activity level with Time-Use-Survey, and on the other hand at the load profile level with the CREST model and based on metered load profiles. The first part of this objective has been met: the analysis showed some clear differences between groups and countries, revealed by the empirical data, which are a reminder of the importance of non-energy policy (e.g. school hours) in determining peaks. As well as encountering useful insights into international differences in energy-related behaviour, the results showed some key differences within specific socioeconomic groups, such as single persons, families with children, and pensioners. The second part of the second objective could not yet be met. The German metered dataset (Hoffmann et al. 2015) was found to contain anomalies so that for the present purpose it was ultimately rejected. The UK dataset (Schofield et al. 2015) is indeed extensive and rich, but the lack of a suitable method of household characterisation means that this analysis is outstanding. Preliminary work indicated that a simple binary classification of households into categories such as ‘retired’ does not seem conducive to a comparison, as the resulting groups are associated with large variance and limited differences in terms of median and mean.

These and other aspects will be addressed in further work. The further work will focus on extending the German CREST model to include a German appliance stock, as well as allocating these appliances according to households’ socioeconomic characteristics. The definition of the groups themselves needs to be refined, as already mentioned, perhaps to include multiple variables and based on clustering or similar techniques. A further question is raised about what quantitative metric to employ in order to compare inter- and intra-group profiles – one option would be to employ load indicators such as daily peak, time and extent of peak, etc. Once these issues are addressed, the ‘validation’ with smart meter data can be attempted. Finally, this paper focused on baseline issues, i.e. variation of existing residential load profiles and time use activities. The consideration of flexibility could also be incorporated, by classifying appliances according to their suitability for this. This might also require a modified activity type structure in the CREST model, and would enable an international comparison of (technical) flexibility potentials in specific socioeconomic groups.

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