How do household activities drive electricity demand? Applying activity-based modelling in the context of the United Kingdom

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DECLARATION OF INTERESTS
The authors declare no competing interests.

HIGHLIGHTS

- Activity-based frameworks offer a means of modelling demand side response (DSR).
- A log-linear mixed-effects model of household energy demand is proposed.
- The model reflects household activities alongside conventional variables.
- The model is operationalised using residential electricity demand data from the UK.
- Forecasting of activities' marginal change in electricity consumption is presented.

ABSTRACT

Driven by the necessity to increase utilisation of the existing networks and accommodation of volatility in renewable energy generation, the energy sector is undergoing a shift from an unconstrained infrastructure expansion to accommodate growth in demand towards demand management strategies. Such strategies, for example nudging demand using incentives such as price signals, or Demand Side Response (DSR), rely on the ability to accurately understand and harness flexibility in demand. Activity-based demand modelling frameworks can provide this capability, as they enable the detailed modelling and simulation of individuals and their activities. However, to date, no modelling approach has been proposed that can link energy consumption of a household to the activities undertaken, heterogeneity of the household residents, presence and use of household appliances and devices as well as weather and energy system-related variables. This paper addresses the gap by proposing a log-linear mixed-effects model of energy consumption based on reported household activities alongside a comprehensive set of attributes and contextual variables that might influence household energy consumption. Application of the model is demonstrated using joint time-use and residential electricity consumption data from 160 households, collected between 2016 and 2018 in the UK. The modelling results prove the value of incorporating time-use (activities) in modelling residential electricity demand, when compared against modelling without such considerations. Furthermore, the model provides (semi-)elasticities of demand and marginal changes in electricity consumption due to activities, which are of direct policy value or serve as inputs into activity-based energy demand simulation.

Keywords: Activities, DSR, Energy demand, Regression, Time use

1. INTRODUCTION: ACTIVITIES AND THEIR ROLE IN SHAPING ENERGY DEMAND AND THE DEMAND-SIDE RESPONSE

The energy sector is undergoing a transformation where a 'predict and provide' response to addressing energy needs is increasingly being complemented or replaced by demand management strategies. This is driven by the necessity to increase utilisation of the existing networks (for example due to the widespread electrification of transport) but also to accommodate uncertainties and volatility associated with the shift towards renewable energy generation [1,2]. Demand management strategies are focused on achieving an alignment between the demand and supply, typically using price signals, through adjustment in the demand (lowering energy demand and/or shifting the demand from peak hours), assuming that the demand is flexible and responsive to policies and incentives. The effectiveness of such Demand Side Response (DSR) policies relies, however, on the ability to accurately understand and harness flexibility in the demand.

The underlying assumption for DSR policies is that there are price-based interventions such as time-varying pricing or non-price interventions, e.g. feedback and social comparison which can make agents (individuals, companies, but also smart appliances) change their energy consumption patterns [3,4]. Since energy is a derived demand, the source of that flexibility will therefore derive from flexibility in the activities which the energy is consumed for or from the associated use of appliances and devices (whether operated by the agents or by automated controllers[1]). In other words, energy is consumed to undertake activities, and not for its own sake. An increase in the price of energy thus increases the cost of undertaking certain activities with a higher energy footprint. Hence, an activity-based modelling approach, in which an individual allocates time to an activity and schedules it for a particular time of day, appears to be a natural tool for behaviourally realistic modelling of the DSR [5]. The key to such an approach is the ability to forecast activities, their scheduling and the ability of individuals to adapt the schedule given various incentives [6]. Energy demand can then be derived from an activity-based modelling approach by linking activities to their associated energy footprint (intensity) and thus estimating the corresponding energy consumption of the household. While in the past, aggregate models of energy use based on household archetypes could be accepted, in a world where generation is much more volatile and storage can be dynamic and regulated by pricing, there is an urgent need for models of energy demand that are also more dynamic. Such models should reflect the behaviour of individuals, especially interactions with their appliances, as lifestyles become more and more 'electrified'.

The relationship between activities and energy demand has recently become an active field of research [7–9]. The recent efforts to produce high-resolution end-use energy demand profiles using bottom-up approaches has highlighted the role of activities in overall demand profiles [10,11]. A stream of research efforts has explored activity participation to understand flexibility in energy demand. Specifically from the DSR viewpoint, these studies have mostly shed light on contributors to demand peaks, and types of activities (and their associated energy consumption) that are flexible [12,13]. These studies have shown that activities can be flexible or inflexible in terms of activity timing and location. For example, while seasonal variation exists, lighting and heating/cooling of rooms are inflexible in terms of energy consumption. Such consumption, however, is relatively easy to predict as it usually follows a cyclical pattern [14]. On the other hand, an example of a flexible activity is laundering, which has relatively good flexibility in terms of the time of day and the day of week when it needs to be undertaken. Work is another example of an activity that can be flexible for some workers in terms of both timing and location, especially given the recent growth of working from home and flexible job schemes. Smale et al. [15] categorise activities in terms of

[1] In the current study, we focus on the behavioral side of energy demand flexibility due to its close link to activity participation. While not discussing it in detail, we note that demand flexibility can also derive from infrastructure and technology capabilities that can shift energy consumption and still achieve the desired outcomes. Examples include thermostats (especially for buildings with high thermal inertia) that can ensure thermal comfort of residents while shifting energy consumption or smart appliances that can complete tasks, e.g. (dish-)washing, laundry, by specified time.

their flexibility and indicate that timing is inflexible for lighting, heating and cooling spaces, is critical and almost inflexible for cooking/eating and leisure activities, and is flexible for domestic cleaning practices. Friis and Christensen [16] showed that households indeed would shift the timing of their dishwashing, laundering and electric vehicle (EV) charging activities in response to time-varying pricing schemes. Their study was limited in terms of sample size but demonstrated that at least a portion of population would be responsive to price signals or as shown in other studies to non-price interventions highlighting the DSR strategies could play in changing energy demand [4].

Several studies have investigated the use of time-use diary data to estimate the flexibility potential of daily activities and their implications for time-shifting energy demand practices [17–21]. Such studies generate synthetic activity sequences for individual households and convert those activities to domestic electricity demand using assumed activity-to-power conversion factors [22,23]. Validation of modelled electricity demand from such models against observed power measurements showed that such a model can produce highly realistic hourly load patterns with preservation of important qualitative features including end-use composition and diversity between households as well as annual and diurnal variations. Due to the lack of combined data of activities and energy consumption, these studies typically assume the energy intensity of activities. Thus, the estimated energy demand could be limited as various influencing factors might have been neglected. For example, the energy intensity of activities might be different between or within households depending on contextual factors such as weather and time of day attributes, household characteristics such as house type, type of appliances in the house, and the number of people in the household, or energy system variables such as the energy pricing scheme. Ignoring such heterogeneity

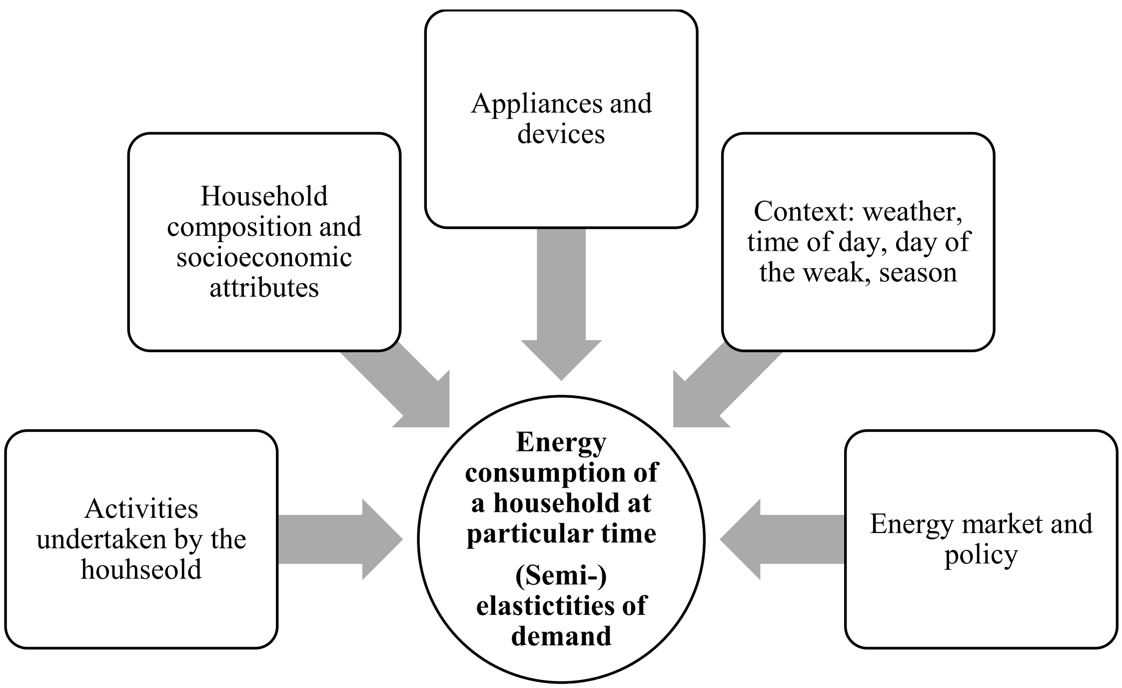

Fig. 1. Conceptual representation of the proposed modelling approach

might result in biased estimates of energy demand and demand side responses to different policy scenarios, especially if the sources of heterogeneity are correlated with the demand side response.

Other studies have focused on identifying activities from energy (electricity) consumption through load disaggregation and non-intrusive appliance load monitoring techniques [24,25]. However, only a handful of studies have tried to quantify energy intensity (sometimes referred to as footprint) of specific activities using data collected from both household activities and household energy consumption mostly in the form of smart meter readings of electricity consumption [26,27]. Such a combined dataset provides an ideal opportunity to link household activities to their associated energy consumption and calculate more accurate estimates of the marginal change in electricity consumption due to the activity undertaken in the household. For example, Grunewald and Diakonova [27] collected data from more than 300 households who reported over 18,000 activities along with minute-by-minute readings of smart meter electricity consumption (called the METER dataset). Using this dataset and household base-loads (the minimum consumption typically comprising stand-by devices and other continuous loads), Grunewald and Diakonova [28] proposed the concept of marginal electricity demand which quantifies the contribution of specific activities to electricity demand. Their analysis demonstrates that electricity consumption is strongly related to the activity patterns. However, their analysis is based on a simple direct regression model and ignores many other contributing factors such as weather, household attributes and the electricity pricing scheme.

At the same time, shortcoming exists in modelling approaches that quantify links between energy consumption of a household and activities undertaken by the residents. In particular, the existing approaches assume intensity values associated with activities, instead of seeking to estimate them from available data. Moreover, such approaches do not provide guidance concerning how such intensities may vary depending on the household composition, time of day, weather variables or energy pricing. These shortcomings may make activity-based modelling less effective, especially for approaches requiring high-resolution demand predictions, e.g. in DSR modelling. To address these gaps, the present paper aims to build an appropriate methodology for activity-based modelling of energy consumption in residential contexts. Three specific research questions stem from this aim. The first question concerns how to model impacts of activities of household members on the overall household energy consumption, but without assuming a priori the energy intensities of specific activities. The second question concerns how to model such impacts jointly with other drivers of consumption, including attributes of the household (and its members), presence and use of appliances, weather or energy policy-related factors. Finally, the third research question concerns the use such framework to estimate marginal changes in energy consumption due to activity participation, given the overall context in which they take place.

To address these research questions, the study proposes a regression-based methodology for inferring activity-specific intensities from data that jointly observes time-use and energy consumption, while accounting for a comprehensive set of attributes that might influence household energy consumption (Figure 1). The joint consideration of the groups of factors outlined in Figure 1 stems from research reporting on their role in shaping energy demand profiles, including household attributes [8,24], activities [12,20,23], appliances and devices [9,10,14], context [17,21,23] as well as energy market and policy [15,16]. As a proof of amenability to empirical operationalisation, the model is calibrated using a dataset from the UK that holds simultaneous information on electricity consumption and time-use (see section 2). Whilst the sample specificity and limited size affect the empirical results, the obtained values are broadly in line with expectation. While the present empirical focus is on the demand for electricity, the method is designed to be generalisable to other types of energy and public utilities, following a similar protocol of analysis.

The remainder of this paper is structured as follows. Section 2 presents the empirical data used in the current study, including its processing and descriptive analysis. Section 3 introduces the modelling framework, including its operationalisation for the current empirical context. Section 4 presents and discusses the modelling results, including presentation of application of the framework to estimating marginal changes in electricity consumption due to activity undertaking. Section 5 concludes the paper and provides an outlook for the future research directions.

2. DATA: PROJECT METER

The data used in this study covers the period of 2016-2018 and is obtained from the Project METER (https://www.energy-use.org/), which collects simultaneous information on energy consumption and time-use [29]. The METER dataset is unique and innovative in that it allows analysis of the relationship between activities and energy consumption.

Participating households in Project METER were recruited across the United Kingdom (UK) as part of a campaign conducted online, via radio and at selected community events [27]. Their participation was incentivised by offering a chance to win the cash equivalent of a year's worth of electricity. The specific nature of the study and recruitment was deemed to lead to an overrepresentation of high income groups as well as energy-aware individuals such as adopters of particular energy and electric vehicle technologies (see section 2.2). Individual and household characteristics including socio-demographic information were collected during the registration. The study allowed household members above the age of eight to participate. Each participating household was given a choice of 3 randomly assigned dates. For the selected date, activity and electricity recordings were taken over a 28 h period starting at 5pm, so that two of the typically most energy intensive periods between 5pm and 7pm could be captured [27].

Participating households were sent a parcel containing the electricity recorder, activity recorder(s) and an instruction booklet. The electricity recorder was clamped by the participants themselves below the household's electricity meter to take readings up to every second. Activities, on the other hand, were recorded using a dedicated app, pre-installed on purpose-built devices sent alongside the electricity recorder. The app guided users through a series of questions, concerning their location, activity type and the number of other people participating in the activity. While the users were encouraged to report activities at the time, they could also add them retrospectively or into the future. Each user selection is recorded with one of 144 time-use codes, consistent with the UK Time Use Survey 2014-15 [30]. As activities were recorded for all household members, the data crucially permits analysis of the time use patterns of the entire household and their joint participation in activities, as well as their links to energy consumption. A more detailed description of the functionality of the app and the data collection process is available in [27,31].

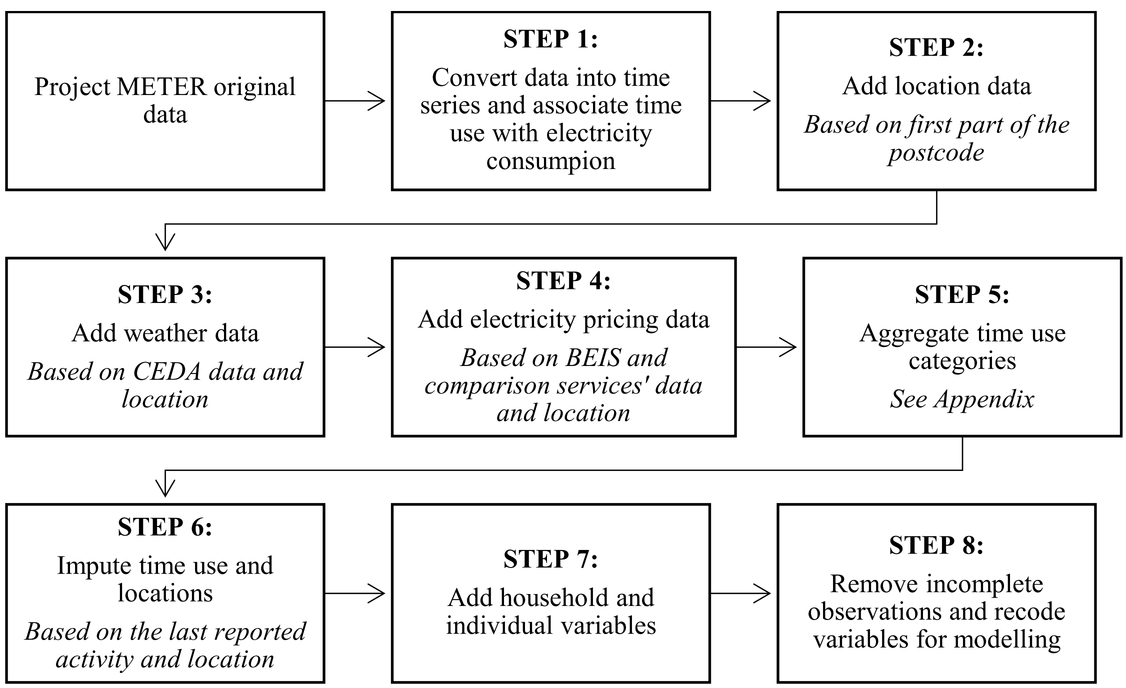

Fig. 2. Data processing steps

2.1 DATA PROCESSING

The data from Project METER underwent significant processing to enable its use for the present modelling context, as outlined in Figure 2. In step 1, the energy consumption data was converted into date- and time-stamped series. The date-time stamps were used to match electricity readings with specific activities reported by individuals in their time use diaries. In step 2, the data was supplemented with the first part of the household postcode from the original database, so as to preserve the respondents' privacy and compliance with the data use policy. In step 3, based upon the location information added in step 2, weather data was added for each household during their reporting period, based on the nearest MIDAS (Met Office Integrated Data Archive System) weather station, for which suitable historical data was available from the Centre for Environmental Data Analysis (CEDA) [32]. In step 4, the data was further supplemented with energy pricing, drawing upon the annual energy price data from consumer price indices for fuels [33], tariff comparison service UKPower (www.ukpower.co.uk) and sources describing conditions of the economy tariffs in the UK [34,35]. In step 5, activity categories were aggregated to enable reasonable estimation and prevent identification issues during estimation. In step 6, the processing addressed the most substantial shortcoming of the dataset, namely absence of reported end times of the activities. Hence missing values (activity types, their locations and number of participants) were imputed using the most recently reported activity. For example, if activity A was reported at 10:00 followed by activity B reported at 10:45, time between 10:00 and 10:45 was assumed to be spent in activity A. In step 7, household and individual attributes were added to the dataset. Lastly, in step 8 incomplete observations were removed whilst the variables were recoded so as to facilitate subsequent modelling routines, including transformation of categorical variables into binary variables and removal of observations with missing information, e.g. household attributes or energy consumption. The data processing was implemented in RStudio and used a number of routines from packages dplyr [36], forecast [37], lubridate [38], smooth [39], zoo [40].

2.2 DESCRIPTIVE ANALYSIS

The final sample consisted of 160 households from across the UK (excluding Northern Ireland), whose descriptive statistics are presented in Table 1, against (limited) descriptive statistics for the previous study using METER data [28] and the national statistics reported there. Importantly, the composition of the present sample is different to that in the aforementioned previous study using METER data as a result of the data processing, including exclusion, as outlined in section 2.1 We opt for a more detailed presentation to support subsequent modelling efforts. As can be observed from Table 1, the current sample offers good distribution in terms of different household sizes, income levels and residence types. The sample composition with respect to household sizes resembles that of the previous analysis and the national shares. As for the income distribution, both current and previous METER study samples have a higher share of households with income above £50k per annum. As for the appliances and devices, the current sample contains a higher share of households with an EV, photovoltaic panels or dishwasher when compared to the previous METER study, itself above the national average. The levels above national average are likely to be reflection of the sample bias towards individuals interested in the topic of energy, with those owning PV or EVs appearing to provide most complete data and hence included in the present analysis. Whilst this may limit the representativity of the analysis, it is beneficial for modelling efforts, in which balanced shares facilitate parameter estimation, especially for samples of limited size.

Table 1. Descriptive statistics of the sample (n=160 households)

Variable	Current analysis		Previous METER study (%)[a]	National (%)[b,c,d]
	Number	%		
Region			n/a	n/a
East England	2	1.3	n/a	n/a
East Midlands	2	1.3	n/a	n/a
East of England	18	11.3	n/a	n/a
Greater London	21	13.1	n/a	n/a
North East	4	2.5	n/a	n/a

Table 1. Descriptive statistics of the sample (n=160 households)

Variable	Current analysis: Number	Current analysis: %	Previous METER study (%)[a]	National (%)[b,c,d]
North West	9	5.6	n/a	n/a
Scotland	7	4.4	n/a	n/a
South East	69	43.1	n/a	n/a
South West	18	11.3	n/a	n/a
Wales	4	2.5	n/a	n/a
Household size			n/a	n/a
1 (single occupant household)	26	16.3	57	64
2	70	43.8		
3	27	16.9	37	30
4	32	20.0		
5	3	1.9	2	7
6	2	1.3		
Employed household members				
0	47	29.4	n/a	13.6
1	60	37.5	n/a	86.4
2	52	32.5	n/a	
3	1	0.6	n/a	
Annual household income				
Below £15k	11	6.9	6	19
£15k-25k	18	11.3	13	22
£25k-35k	19	11.9	9	16
£35k-50k	25	15.6	21	17
£50k-70k	41	25.6	51	27
Above £70k per annum	46	28.8		
Residence type				
Flat/apartment	26	16.3	n/a	20.2
Detached house	43	26.9	n/a	17.1
Semi-detached house	37	23.1	n/a	25.5
Terraced house	40	25.0	n/a	28.0
Bungalow	6	3.8	n/a	9.2
Other	8	5.0	n/a	-
Appliances and devices				
Electric vehicle (EV)	10	6.3	4	.4
Solar thermal	18	11.3	n/a	n/a
Photovoltaic (PV) panels	40	25.0	14	4
Electricity display	29	18.1	n/a	n/a
Electric hob	55	34.4	n/a	n/a
Heat pump	7	4.4	n/a	n/a
Gas boiler	124	77.5	n/a	n/a
Underfloor heating	34	21.3	n/a	n/a
Washer dryer	23	14.4	99	97
Tumble dryer	52	32.5		
Washing machine	157	98.1		
Dishwasher	90	63.6	51	45
Dehumidifier: number of units (mean: .188, std. dev.: .437)				
0	133	83.1	n/a	n/a
1	24	15.0	n/a	n/a
2	3	1.9	n/a	n/a
Air conditioner: number of units (mean: .063, std. dev.: .290)				
0	152	95.0	n/a	n/a

Table 1. Descriptive statistics of the sample (n=160 households)

Variable	Current analysis		Previous METER study (%)[a]	National (%)[b,c,d]
	Number	%		
1	6	3.8	n/a	n/a
2	2	1.3	n/a	n/a
Portable heater: number of units (mean: .350, std. dev.: .636)				
0	117	73.1	n/a	n/a
1	31	19.4	n/a	n/a
2	11	6.9	n/a	n/a
3	1	.6	n/a	n/a
Night storage heaters: number of units (mean: .100, std. dev.: .563)				
0	153	95.6	n/a	n/a
1	3	1.9	n/a	n/a
2	2	1.3	n/a	n/a
3-5	2	1.3	n/a	n/a
Power shower: number of units (mean: .313, std. dev.: .646)				
0	123	76.9	n/a	n/a
1	27	16.9	n/a	n/a
2	7	4.4	n/a	n/a
3	3	1.9	n/a	n/a
TV or computer screens: number of units (mean: 2.719, std. dev.: 1.606)				
0	5	3.1	n/a	n/a
1	27	16.9	n/a	n/a
2	44	27.5	n/a	n/a
3-5	79	49.4	n/a	n/a
6-8	3	1.9	n/a	n/a
9-11	2	1.3	n/a	n/a
Energy tariff				
Standard	79	49.4	n/a	n/a
Economy7	15	9.4	n/a	n/a
Economy10	2	1.3	n/a	n/a
Green	42	26.3	n/a	n/a
Other	22	13.8	n/a	n/a

[a]As reported in Table 1 in Grunewald and Diakonova (2019)[28]
[b]Derived from several sources as reported in Table 1 in Grunewald and Diakonova (2019) [28]
[c]ONS (2019)[41]
[d]MHC&LG (2019)[42]

In general, among the appliances, except for the heat pumps, air conditioners and night storage heaters, we observe shares above 10%. For the appliances for which number of units was recorded, we observe that households would tend to own single units of dehumidifiers, air conditioners, portable heaters, night storage heaters or power shower units. An exception are TV or computer screens, where most respondents would own between 3 and 5 screens, with only a handful of households not owning even a single screen. As for the distribution of energy tariffs, majority of respondents reported being on a standard tariff, followed by green and other tariffs. Only about 11% of respondents reported being on an Economy tariff, which is below the level of 15% indicated in the report by department for Business, Energy & Industrial Strategy (BEIS) [43], with no official data available for the Green Tariff for the period.

Table 2 presents a summary of the distribution of activities conducted at home and reported by the households within the sample used for model estimation (see section 3.2 for a detailed description of how the model estimation sample was obtained). Note that different household members could have undertaken some of the activities simultaneously within the household, hence the percentages sum up to more than 100%.

Table 2. Descriptive statistics of the sample: episodes for the (n=7587 episodes)

Activity	Number of episodes	%age
Work	8	.1
Sleep	144	1.9
Home care	480	6.3
Personal care	798	10.5
Study	2	<.1
Leisure	1231	16.2
No occupant present and activity reported	4981	65.7

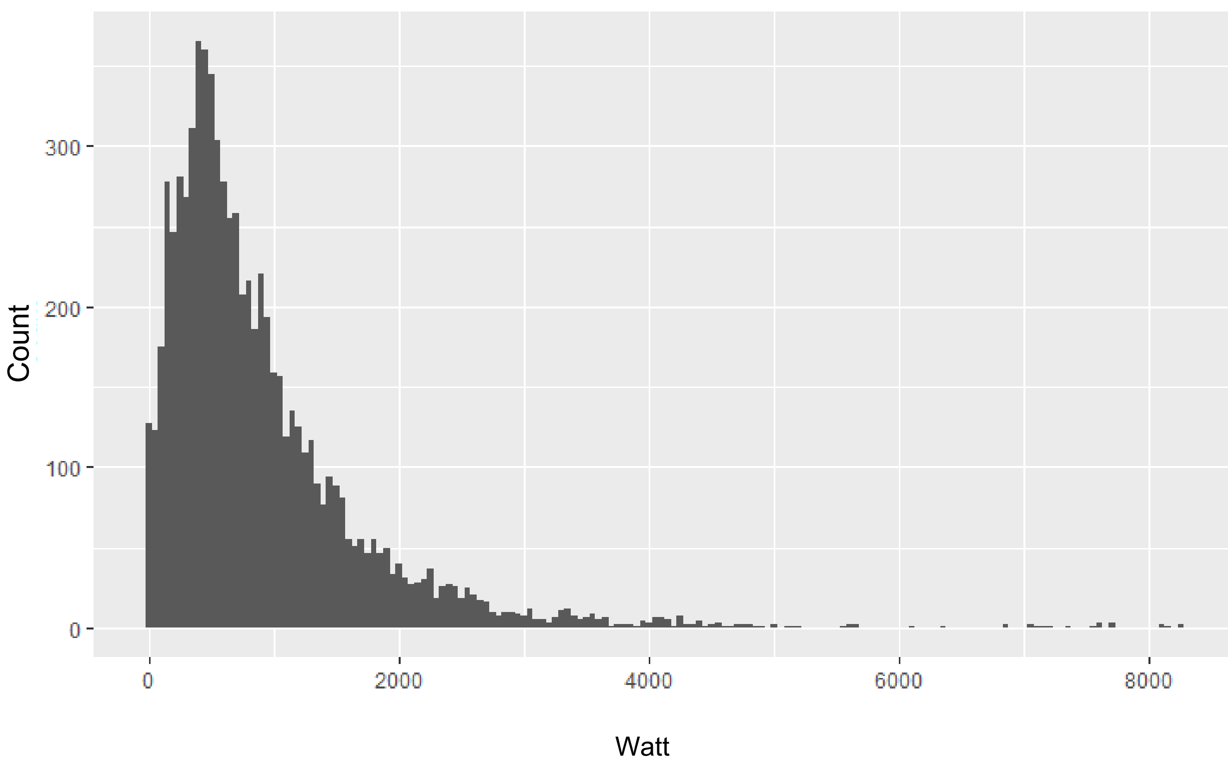

Fig. 3. Histogram of electricity demand (moving average, s=20) observed in the sample (n=7587 readings)

As for the reported demand for electricity in the sample, Figure 3 presents a histogram of moving averages[2] (s=20) derived from the observed readings in the sample used for the model estimation. The values range from the minimum of 1.9 Watt to the maximum of 8253.2 Watt, with the observed mean of 900.5 Watt and the standard deviation of 837.2 Watt. 89.1% of reported values are below 2 kilowatt while 96.1% of values are below 4 kilowatt demand.

The current sample as can be seen in Table 1 is not nationally representative. Nonetheless, it is believed that the sample, unique in jointly containing time-use and electricity demand, retains the fundamental relationships between the variables of interest, even if their magnitude may not be representative for the entire population. Quantifying the latter to obtain benchmark values for use in a more generalised context,

[2] The motivation for using a moving average in the present analysis is explained in section 3.2.

however, would be a further step supported by evidence for successful operationalisation of the proposed model in the present, more specific context.

3. THE MODELLING FRAMEWORK

The following section presents an approach to addressing the need for modelling household residential energy consumption, taking into account presence and activities of the dwellers as well as other contextual factors. Section 3.1 outlines the proposed model while section 3.2 presents the empirical data used for its estimation, alongside its suitable processing for use in the current context. Importantly, the present empirical application serves as a proof of amenability of the proposed approach to empirical application. Towards that end, its primary purpose serves to establish that the proposed framework can be operationalised in a real-world context, leading to meaningful parameters broadly in line with intuition. The actual magnitudes of the parameters should be of secondary consideration, being inherently affected by the data specificity and limited sample size.

3.1 GENERAL MODELLING FRAMEWORK

In order to estimate the effect of activity participation on household residential energy consumption, we propose a regression model that relates the logarithm of the consumption (assumed positive) to a comprehensive set of exogenous covariates describing the household and its members, activities undertaken by them, appliances in use, energy tariff and cost as well as weather conditions. The most general formulation takes the form of a linear panel data model (REF) of the following form [44], which includes both fixed and random effects (Eq.1):

$$
\begin{aligned}
\log g(\pi_{kt}) = {} & \beta_{0kt} + \sum_{h=1}^{H} \beta_h X_{kh} + \sum_{i=1}^{I_k} \left(\left(1 + \beta_{\delta i} \delta_{ki_t}\right) \sum_{j=1}^{J} \beta_i X_{kij} \right) + \sum_{a=1}^{A} \left(\beta_{a0} \delta_{ka_t} + \beta_a X_{ka_t} \right) \\
& + \sum_{d=1}^{D} \beta_d \delta_{kd_t} + \sum_{w=1}^{W} \beta_w X_{kw_t} + \sum_{e=1}^{E} \beta_e X_{ke_t} \\
& + \sum_{q \in \{H,J,A.D,W\}} \sum_{r \in \{H,J,A.D,W\} \setminus q} \delta_{qr} \beta_{qr} X_{kq_t} X_{kr_t} + \mu_k + \varepsilon_{kt}
\end{aligned}
\qquad \text{Eq.1}
$$

where

π_{kt}	reported energy consumption rate of household k at time t;
$g(.)$	function which converts the reported energy consumption at time t to the one to be regressed against, potentially controlling for inaccuracy of reporting;
X_{kh}	household's k attribute h from the set of H attributes;
X_{kij}	household's k individual ith attribute j from the set of J attributes;
X_{ka_t}	number of individuals participating in activity a, reported at time t at household k;
X_{kw_t}	weather and season variable w from the set of W variables, reported at time t at the residence of household k;
X_{ke_t}	energy market and policy variable e from the set of E variables, reported at time t by household k;
δ_{ki_t}	indicator (dummy) variable that has the value of 1 if household's k individual i is at home at time t within the household 's residence and 0 otherwise;
δ_{ka_t}	indicator (dummy) variable that has the value of 1 if activity a is reported at time t within the residence of household k and 0 otherwise;

δ_{kd_t}	indicator (dummy) variable that has the value of 1 if device d is in operation at time t at household's k residence and 0 otherwise;
δ_{qr}	indicator (dummy) variable that has the value of 1 if interaction term between variables q and r is present in the model and 0 otherwise;
$\beta_{\dots}$	coefficients of the model, with β_{0kt} an intercept term and otherwise as indicated by the subscript;
μ_k	household-specific, time-invariant econometric error term;
ε_{kt}	household-specific time-variant econometric error term.

The model relates household residential energy consumption (left-hand side of Eq.1) to a number of covariates that have been variously shown to or are hypothesised to affect it, as previously indicated in section 2. In particular, the right-hand side of the equation allows for the consumption to be correlated with household attributes, weather conditions and energy variables, all possibly time-dependent. In addition, the RHS includes representation of the household member attributes, distinguishing between the effect of being a member of the household versus being present at particular time, as captured by the indicator variable δ_{i_t}. Furthermore, the RHS can represent activities undertaken in the households and the devices in operation, naturally allowing for those to vary across time. Finally, in line with Leroy and Yannou (2018) [8], the model allows interactions between the variables above, to account for the possibilities of the impacts to be related to a particular combination of sociodemographic and other circumstances, such as late time of day requiring more lighting to undertake an activity or household size affecting energy consumption from cooking, cleaning or washing.

Importantly, the model does not impose restrictions on simultaneous operation of multiple appliances or conduct of activities. While the relevance of the former is obvious, the latter captures both the possibility of different household members participating in different activities at the same time as well as of multitasking, i.e. an individual participating in more than one activity at the same time. Hence, the novelty of the proposed modelling framework lies in its considerable flexibility of accommodating all the above factors jointly, while also allowing a substantial sophistication in the representation of the presence and time-use of the household members.

Finally, formulation of the model as a log-linear regression yields a very convenient interpretation of its parameters [45] as elasticities for covariates X expressed as natural logarithms of the quantities of interest X^*, i.e. $X = \log X^*$ (note that the expression may also involve terms associated with interactions between covariates):

$$\zeta_{X^*} = \frac{\%\Delta g(\pi_{kt})}{\%\Delta X^*} \approx \frac{\partial \log g(\pi_{kt})}{\partial X} = \frac{\partial \log g(\pi_{kt})}{\partial \log X^*} = \beta_X + \sum_{r \in \{H,J,A.D,W\} \setminus X} \delta_{Xr}\beta_{Xr}X_r \qquad \text{Eq.2}$$

or semi-elasticities for quantities for which percentage change may not have a natural meaning or interpretation:

$$\zeta_X^{semi} = \frac{\%\Delta g(\pi_{kt})}{\Delta X} = \frac{\partial \log g(\pi_{kt})}{\partial X} = \beta_X + \sum_{r \in \{H,J,A.D,W\} \setminus X} \delta_{Xr}\beta_{Xr}X_r \qquad \text{Eq.3}$$

The latter may be especially useful in the present context, where discrete ordinal (household size, number of appliances) or categorical variables (residence type, month of observation) warrant an expression not relying on the assumption of continuity of the variable.

3.2 MODEL OPERATIONALISATION

The temporal dependence of the model in Eq.1 suggests natural operationalisation to be time-series based, e.g. such as linear regression panel analysis (to account for presence of households) or a class of the ARMAX (Autoregressive integrated moving average with exogenous variables) models [45,46]. However, as outlined in section 2.1 (step 6 of data processing), the currently available data does not permit a straightforward time-series-based operationalisation, due to activity reporting being available only for the start times (with rare exceptions). Nevertheless, the general formulation from Equation 1 can be adapted to be ‘event driven’ by the activity reporting time, i.e. estimate the coefficients in the vicinity of the activity reporting time, with times $\hat{t}$ indicating points for which observations of variables of interest, such as activities, are available.

In addition, since we do not know the duration of appliance use, the time-dependent variables associated with appliance operation is replaced by time-invariant proxies δ_{kd}, expressing presence of the appliance in the household. The remaining variables are as previously described, though with reference to times $\hat{t}$. The intercept β_{0kt}= β_0, i.e. is assumed to be common across the households and episodes. Similarly, the error component ε is assumed to be identically distributed across households and reported activities, i.e. $\varepsilon_{k\hat{t}} = \varepsilon$ for all k and $\hat{t}$. When imposing such assumptions on model presented in Eq. 1, the resulting formulation is effectively a mixed-effects model (Eq.4) [45]:

$$\begin{aligned}\log g(\pi_{k\hat{t}}) = \beta_0 &+ \sum_{h=1}^{H} \beta_h X_{kh} + \sum_{i=1}^{I_k} \left(\left(1 + \beta_{\delta i} \delta_{ki_{\hat{t}}}\right) \sum_{j=1}^{J} \beta_i X_{kij} \right) + \sum_{a=1}^{A} \left(\beta_{a0} \delta_{ka_{\hat{t}}} + \beta_a X_{ka_{\hat{t}}}\right) \\ &+ \sum_{d=1}^{D} \beta_d \delta_{kd} + \sum_{w=1}^{W} \beta_w X_{kw_{\hat{t}}} + \sum_{e=1}^{E} \beta_e X_{ke_{\hat{t}}} \\ &+ \sum_{q \in \{H,J,A.D,W\}} \sum_{r \in \{H,J,A.D,W\} \setminus q} \delta_{qr} \beta_{qr} X_{kq_{\hat{t}}} X_{kr_{\hat{t}}} + \mu_k + \varepsilon \end{aligned} \qquad \text{Eq.4}$$

As for the function $g(.)$, we propose it to account for the possible inaccuracies in reporting of time-dependent covariates, particularly undertaking an activity (but possibly also operating a device or in the number of participants in an activity), as reported by the individuals. Where no error in activity reporting exists, it could be possible to directly rely on the energy consumption measurements (Eq.5):

$$g_1(\pi_t) = \pi_t \quad \forall\, t \qquad \text{Eq.5}$$

Grunewald and Diakonova [27] found, using the same dataset as in the current study, that individuals reported 67% of their activities within a 10 min accuracy. This suggests the need for a method to smoothen the set of readings. To address this issue, we propose the use of a moving-average of energy consumption measurement in the vicinity (S periods before and after) of the reported time (Eq.6):

$$g_2(\pi_{\hat{t}}) = \sum_{k=s}^{S} \omega_s \left(\pi_{\hat{t}+(s-1)} + \pi_{\hat{t}-(s-1)}\right) \qquad \text{Eq.6}$$

Where ω_k is a relative weight attached to measurements in the $t-(s-1)$th and $t+(s-1)$th period. For a standard moving average approach, which is followed in this paper, this means:

$$\omega_s = \frac{1}{2S} \quad \forall\, s \in S \qquad \text{Eq.7}$$

This raises a natural question regarding the choice of S, i.e. periods before and after, over which the measurement is averaged. Assuming that the misreporting follows a normal distribution, the Grunewald and Diakonova finding that 67% of individuals report their activities within a 10 min accuracy roughly coincides with the fraction of observations falling within one standard deviation of a normal distribution. Hence, in the absence of other evidence, we argue that setting S to 20 should cover approximately 95% of true activity start times while not causing much confounding between subsequent activities.

The resulting model can be interpreted as a mixed-effects model, with the impacts of covariates captured as 'fixed effects' and the error components μ_k and ε representing 'random effects'. From another point of view, the model represents a hierarchical model, due to the presence of individual readings and variables grouped into household variables. Importantly, the formulation acknowledges this data structure in the form of presence of the error terms, μ_k and ε in the formulation [45]. Moreover, estimation of the parameters requires accounting for this hierarchy to obtain unbiased estimates of standard errors and allow suitable inferences. For this purpose, a generalised least squares approach is recommended as being free from distributional assumptions and offering closed-form solutions [44,45], and in the current instance it is performed using the 'plm' package in R [47].

3.3 MODEL SPECIFICATION

In order to address the posed research questions, we propose three specifications. Model 1 serves as a benchmark that incorporates conventional variables describing drivers of residential energy demand. It excludes time-use related considerations (activities) or interaction variables. The purpose of this specification is to establish a baseline model, using the present data, against which to assess more sophisticated specifications, in terms of their goodness-of-fit, parameter stability and additional behavioural insight. Due to nature of this specification and the need to balance against a limited sample size (effectively number of households), we had to make decisions concerning incorporation of variables based on both theoretical (known drivers or their proxies, policy relevance) and statistical (parameter significance, increased model fit, stability of other parameters) grounds. Table 3 summarises variables tested in the specification, including those deemed essential for control and policy purposes that were forced into the model and optional ones, incorporated only if sufficient statistical evidence was found (typically p-value <.100 and absence of non-convergence, inflated parameter values and standard errors in other parameters, signifying possible presence of multi-collinearity).

Table 3. Variables tested in the model specifications

Variable	Reference category	Control / Policy-important	Optional
Household attributes (H)			
Household size	-		●
Number of household members aged:			
Below 8	-		●
8-18	-		●
19-34	-		●
35-50	-		●
51-70	-		●
Above 70	-		●
Annual household income:			
£15k-25k	Below £15k		●
£25k-35k	Below £15k		●

Table 3. Variables tested in the model specifications

Variable	Reference category	Control / Policy-important	Optional
£35k-50k	Below £15k		●
£50k-70k	Below £15k		●
Above £70k per annum	Below £15k		●
Residence type			
Detached house	Flat/apartment		●
Semi-detached house	Flat/apartment		●
Terraced house	Flat/apartment		●
Bungalow	Flat/apartment		●
Individual attributes (J)			
Individual employment status: employed			
Employed	Non-employed	●	
Appliances and devices (D)			
Electric vehicle	-	●	
Solar thermal	-	●	
Photovoltaic (PV) panels	-	●	
Electricity display	-	●	
Electric hob	-	●	
Heat pump	-	●	
Gas boiler	-	●	
Underfloor heating	-	●	
Washer dryer	-	●	
Tumble dryer	-	●	
Washing machine	-	●	
Dishwasher	-	●	
Dehumidifier (number of units)	-	●	
Air conditioner (number of units)	-	●	
Portable heater (number of units)	-	●	
Night storage heaters (number of units)	-	●	
Power shower (number of units)	-	●	
TV or computer screens (number of units)	-	●	
Weather, season, time (W)			
Year	2016		●
Month	February		●
Day of the week	Tuesday		●
Hour of the day (2h slots)	01:00-02:59		●
Air temperature [°C]	-		●
Air temperature^2 [°C^2]	-		●
Dew point [°C]	-		●
Dew point^2 [°C]	-		●
Relative humidity [%]	-		●
Energy market and policy (E)			
Log[a] (price of kWh [0.01£-pence])	-	●	
Log(standing charge [£])	-	●	
Economy tariff (Economy 7 or 10)	Standard tariff		●
Green tariff	Standard tariff		●
Other	Standard tariff		●
Activities in the household (A) (Models 2 and 3 only)			
Work	-	●	
Sleep	-	●	

Table 3. Variables tested in the model specifications

Variable	Reference category	Control / Policy-important	Optional
Home care	-	●	
Personal care	-	●	
Study	-	●	
Leisure	-	●	
Work: Number of individuals involved	-		●
Sleep: Number of individuals involved	-		●
Home care: Number of individuals involved	-		●
Personal care: Number of individuals involved	-		●
Study: Number of individuals involved	-		●
Leisure: Number of individuals involved	-		●
Interaction terms (Model 3 only)	*As main terms*		
Activities in the household			
* Day of the week			●
* Hour of the day			●
* Individual employment status: employed			●
Electric vehicle (EV) in the household			
* Hour of the day			●
Photovoltaic (PV) panels			
* Hour of the day			●
Log(price of kWh)			
* Household income			●

[a] Natural logarithm

The variable groups in Model 1 outlined in Table 3 map onto those in Eqs. 1, 2 and 4 and include household attributes, individual (household member) attributes, weather, season and time, and energy. The quadratic terms for air temperature and dew point were included to capture potential non-linear effects, e.g. increased consumption at low and high temperatures, due to heating, ventilation and air conditioning operation. For variables that take discrete values, the initial reference categories were defined as indicated in Table 3 (which could be different from final reference categories, as will be shown in section 4). For appliances and activities, the reference points are the absence of the respective appliances or non-reporting of the respective activities at the time.

Table 4. Summary of model specifications tested in the study

Variable	Model 1	Model 2	Model 3
Household attributes (H)	●	●	●
Individual attributes (J)	●	●	●
Appliances and devices (D)	●	●	●
Weather, season, time (W)	●	●	●
Energy market and policy (E)	●	●	●
Activities in the household (A)		●	●
Interaction terms			●

Model 2 expands on Model 1 specification by including activity-related variables (though with no interaction terms), in addition to all variables present in Model 1. Model 3, on the other hand, expands on Model 2 specification by further incorporating several interaction terms. These terms include interaction of activity participation with day of the week and hour of the day to seek evidence for how heterogeneity in how energy is consumed in activities depending on when they happen, e.g. mid-day vs evening, weekday vs. weekend. Additionally, interaction of employment status with activity participation is explored, arguably to reveal if professional status affects how energy-intensive activities are. Furthermore, interactions between time of day and presence of electric vehicle and photovoltaic panels are tested. In the former case, the results could serve as a proxy reflection of charging patterns. In the latter, the results can shed light on whether the consumption is aligned with likely generation times (daylight hours). Finally, the interaction between logarithm of electricity consumption price and household income is intended to capture any differences in sensitives to consumption price due to level of affluence.

The specifications are summarised in Table 4. We argue that following this approach provides a means of establishing how incorporation of the additional variables in Models 2 and 3 adds value in terms of insight and fit (confirmed with formal tests), whilst ensuring robustness through comparing stability in control parameters against the base Model 1 specification.

4. RESULTS

The model calibration results are presented in Table 5 (see next page). Section 4.1-4.3 below summarise the goodness of fit, discuss the obtained model coefficients (including control and time-use related variables) and present the results with respect to the marginal change in electricity consumption due to the activity undertaken in the household.

4.1 OVERALL GOODNESS OF FIT AND ERROR TERMS

The overall goodness of fit of the models is reported at the bottom of Table 5 in the form of respective coefficients of determination (R^2) of 0.231 and adjusted coefficients of determination (Adjusted R^2). We can observe that the fit ranges between 0.193 and 0.207 and 0.188 and 0.199 for R^2 and Adjusted R^2. The overall level indicates that there still exists a substantial unexplained inter- and intra-household variation in electricity demand across the households. Furthermore, decomposition of the error terms (similar across model specifications) reveals the value of the intra-household error term variance to be much higher than the idiosyncratic term, which loosely points towards the need for further analyses to incorporate variables capturing the dynamics of processes and activities *within the household* more finely.

Importantly, we observe that Model 3 (incorporating both time-use variables and interaction terms) has the highest fit, followed by Model 2 (time use variables but no interaction terms). In fact, a formal comparison of the respective residual sums of squares using the F tests yields test statistics and p-values that establish superior fit of Model 3 over Model 2 and Model 2 over Model 1. Formally, the results permit rejection of the null hypothesis that models provide the same goodness of fit and thus concluding on Model 3 being the preferred specification. This provides evidence that household activities significantly contribute to shaping of the household energy consumption and that such a contribution may be affected by time of day or household member attributes (via the interaction terms).

4.2 MODEL PARAMETERS

The results of all the model parameters are reported in two groups. Sections 4.2.1 and 4.2.2 discuss coefficients associated with control variables and time-use (activity) variables respectively. It is worth observing that for Model 3 the interpretation of the parameter for a given variable needs to also consider the coefficients associated with interaction terms. While this may increase the difficulty in interpreting the effects of a specific variable, their presence reflects sophisticated relationships between the circumstances underpinning certain levels of electricity demand. Furthermore, the final reference categories as reported in Table 5 may differ from the initial ones assumed in Table 3, in cases of 'Optional' variables (cf. Table 3) where estimated coefficients for some non-reference categories were not found to be statistically significant. Such coefficients were dropped, and categories bundled together with the initial reference category to form the final reference category. Similarly, where values of estimated coefficients were found similar (considering the respective standard errors) and categories permitted natural bundling, a single coefficient was estimated to maintain model parsimony whilst retaining its explanatory power. Once again it is important to reiterate that the presented parameter estimates are based on a rather specific and limited sample, serving primarily to prove the principles of model operation. Hence, caution should be exercised when drawing conclusions from the parameter magnitudes or statistical significance with respect to the postulated relationships holding for a more general population.

4.2.1 Control variables

The first observation upon inspecting control variables in Table 5 concerns parameter stability across the specifications. In particular, the estimated coefficients do not vary significantly between the specifications which provides evidence that the specifications are robust.

Table 5. Estimated model coefficients (*n*=7378 observations from 160 households)

Variable	Coefficients (Standard errors)[a,b]		
	Model 1	**Model 2**	**Model 3**
Household attributes (H)			
Household size	.138 (.071)*	.129 (.072)*	.130 (.071)*
Number of household members aged			
Above 70	.397 (.150)***	.389 (.153)**	.390 (.151)***
Household income per annum (reference: other income levels)			
£25k-35k	.390 (.208)*	.391 (.211)*	.391 (.208)*
Above £70k	.299 (.149)**	.299 (.151)**	.302 (.149)**
Individual attributes (J)			
Individual employment status (reference: not employed, studying, retired)			
Employed	.033 (.090)	.159 (.216)	-.013 (.003)***
Appliances and devices (D)			
Electric vehicle (EV) in the household	.843 (.402)**	.819 (.408)**	.885 (.403)**
* Hour of the day: 09:00-10:59			.259 (.102)**
* Hour of the day: 11:00-12:59			.384 (.138)***
* Hour of the day: 21:00-22:59			-.205 (.080)**
Solar thermal	-.256 (.226)	-.257 (.229)	-.263 (.226)
Photovoltaic (PV) panels	.063 (.068)	.066 (.069)	.067 (.068)
* Hour of the day: 07:00-20:59			.105 (.024)***
Electricity display	.021 (.179)	.025 (.182)	.024 (.179)
Electric hob	.197 (.152)	.186 (.154)	.186 (.152)
Heat pump	.208 (.438)	.212 (.444)	.184 (.438)
Gas boiler	-.352 (.211)*	-.355 (.214)*	-.360 (.211)*
Underfloor heating	.451 (.182)**	.451 (.185)**	.453 (.182)**
Washer dryer	.027 (.283)	.031 (.287)	.029 (.283)
Tumble dryer	-.014 (.157)	-.017 (.159)	-.016 (.157)
Washing machine	.438 (.307)	.450 (.311)	.450 (.307)
Dishwasher	-.151 (.137)	-.146 (.138)	-.148 (.137)
Dehumidifier (number of units)	.188 (.157)	.188 (.159)	.189 (.157)
Air conditioner (number of units)	.230 (.227)	.235 (.230)	.237 (.227)
Portable heater (number of units)	.064 (.109)	.064 (.111)	.064 (.109)
Night storage heaters (number of units)	.044 (.136)	.040 (.138)	.041 (.136)

Table 5. Estimated model coefficients (*n*=7378 observations from 160 households)			
Variable	**Coefficients (Standard errors)[a,b]**		
	Model 1	**Model 2**	**Model 3**
Power shower (number of units)	-.071 (.109)	-.070 (.110)	-.071 (.109)
TV or computer screens (number of units)	.136 (.045)***	.135 (.046)***	.135 (.045)***
Weather, season, time (W)			
Year (reference: 2016 and 2017)			
2018	-.638 (.226)***	-.636 (.229)***	-.647 (.226)***
Month (reference: February, April-July, September, October, December)			
January	.510 (.192)***	.520 (.194)***	.524 (.192)***
March	.376 (.131)***	.375 (.132)***	.386 (.131)***
August	.186 (.105)*	.210 (.105)**	.199 (.105)*
November	.317 (.090)***	.299 (.090)***	.293 (.090)***
Day of the week (reference: Tuesday-Thursday)			
Monday	.110 (.033)***	.104 (.032)***	.103 (.032)***
Friday or Saturday	.275 (.055)***	.276 (.055)***	.284 (.055)***
Sunday	.455 (.074)***	.434 (.074)***	.420 (.074)***
Hour of the day (reference: 01:00-02:59)			
03:00-04:59	-.445 (.189)**	-.419 (.188)**	-.396 (.190)**
05:00-06:59	-.386 (.044)***	-.403 (.044)***	-.383 (.054)***
07:00-08:59			.029 (.038)
09:00-10:59			.003 (.040)
11:00-12:59			.029 (.042)
13:00-14:59			.003 (.040)
15:00-16:59	.074 (.032)**	.082 (.032)***	.095 (.040)**
17:00-18:59	.212 (.021)***	.213 (.021)***	.239 (.032)***
19:00-20:59	.288 (.021)***	.287 (.021)***	.367 (.036)***
21:00-22:59	.093 (.028)***	.099 (.029)***	.142 (.041)***
23:00-00:59	-.172 (.045)***	-.153 (.046)***	-.123 (.054)**
07:00-20:59			.137 (.157)
Air temperature [°C]	-.068 (.013)***	-.068 (.013)***	-.068 (.013)***
Dew point [°C]	.069 (.013)***	.070 (.013)***	.070 (.013)***
Relative humidity [%]	-.012 (.003)***	-.012 (.003)***	-.013 (.003)***
Energy market and policy (E)			
Economy tariff (reference: standard, other)	-.858 (.286)***	-.845 (.290)***	-.856 (.287)***
Green tariff (reference: standard, other)	-.374 (.155)**	-.374 (.157)**	-.376 (.155)**
Log(standing charge)	2.073 (1.495)	2.133 (1.516)	2.183 (1.496)
Log(price of kWh)	-.775 (.071)***	-.789 (.071)***	-.767 (.071)***
Activities (A)			
Work		.027 (.091)	.134 (.216)
Sleep		-.060 (.054)	-.063 (.053)
Home care		.118 (.036)***	.096 (.037)***
* Hour of the day: 15:00-16:59			.279 (.125)**
Personal care		.171 (.029)***	.113 (.044)***

Variable	Coefficients (Standard errors)[a,b]		
	Model 1	Model 2	Model 3
* Hour of the day: 19:00-20:59			-.160 (.054)***
* Individual employment status: employed			.067 (.027)**
Study		-.708 (.426)*	-.699 (.424)*
Leisure		.151 (.025)***	.157 (.027)***
* Hour of the day: 11:00-12:59			.293 (.090)***
* Hour of the day: 19:00-20:59			-.102 (.045)**
Home care: Number of individuals involved		-.063 (.027)**	-.063 (.027)**
Personal care: Number of individuals involved		-.031 (.014)**	-.020 (.015)
Leisure: Number of individuals involved		-.039 (.016)**	-.033 (.017)**
Intercept	2.440 (4.138)	2.311 (4.195)	2.097 (4.141)
Error term variance: idiosyncratic	.358	.355	.351
Error term variance: individual (household-specific)	.530	.545	.540
Number of parameters estimated ($\#(\boldsymbol{\beta})$):	46	55	67
Goodness of fit:			
R^2:	.193	.198	.207
Adjusted R^2:	.188	.192	.199
F statistic vs. Model 1 (p-value)		8.385 (<.001)	7.363 (<.001)
F statistic vs. Model 2 (p-value)			7.057 (<.001)

Table 5. Estimated model coefficients (*n*=7378 observations from 160 households)

[a]Wald test on single parameters, with H0: $\beta = 0$. Significance code key: * .100 ** .050 *** .010

[b]Confidence intervals can be obtained as $CI_{1-\alpha} = \pm SE\ t_{(\alpha/2,\, n-p)}$, where SE is the standard error and $t_{(\alpha/2,\, n-p)}$ is critical value of the t-distribution for upper tail probability $\frac{\alpha}{2}$ with $n - \#(\boldsymbol{\beta})$ degrees of freedom (sample size reduced by the number of estimated parameters).

Looking at household attributes indicates an intuitive result that larger, more affluent households consume more electricity, especially if also having members aged above 70. As for the employment status, we observe that the parameter is only significant for Model 3, where it is also interacted with participation in personal activities (more discussion on this in the next section). What this can point towards is an indication that employed individuals may be absent from home more often and for longer, due to work-related duties, reducing its electricity consumption. This effect is only observed, however, if participation in activities is taken into account. Clearly, it is possible to observe support for the hypothesis that not only size but also composition of the household matters for electricity consumption. We did not find enough evidence for retaining variables related to housing type. Such variables would, in general, act only as a proxy of a combination of the residence size and energy efficiency (built materials, insulation, window types, etc.), both acting in opposite directions in terms of the effect on overall consumption. In absence of more information and statistical support, such variables were excluded from the model.

The next set of coefficients concerns appliances and devices owned by the households. In the current context, only presence, and in some cases the number of units, is analysed. This serves as a readily available proxy for what would be a more desirable, though substantially more difficult (from a data collection standpoint) joint reporting of activities and use of appliances.

The results indicate that the presence of an electric vehicle within a household is associated with a substantial uplift in energy consumption when compared to households without such vehicles, which is entirely intuitive. The interaction with time-of-day variables may be indicative of the charging patterns, revealing higher propensity to charge between 9 and 13, and lower between 21 and 23, as compared to other (reference) times. In absence of the actual charging data, however, we cannot validate whether the model correctly reflects up the prevailing pattern. Nevertheless, the approach demonstrates the principle in which the framework would accommodate the presence and impact of EV on the energy consumption.

Another interesting observation concerns the presence of photovoltaic panels (PV). Specifically, the main effect for such a variable is not statistically significant. However, when interaction with time-of-day variable broadly representing daylight times (7-21)[3], we can observe that consumption during such times is higher than during the remaining times. This observation could be indicative of the alignment (during daylight hours) of consumption to generation, ensuring the most economic use of the PV.

The other statistically significant effects for other appliances are observed for presence of gas boiler, underfloor heating and number of TV units or computer screens. Specifically, households with gas boilers report on average 35-36% lower electricity consumption as compared to those without it. This is unsurprising as absence of gas boiler largely implies use of electricity for heating water (for heating and general use, which inevitably increases the household's electricity demand. In terms of the underfloor heating, its presence is observed to be associated with about 45% higher household electricity consumption as compared to households without it. A potential explanation for this finding is that such systems are either based on electricity ('electric underfloor heating') or requiring heating of a circulating fluid ('hydronic' or 'water' underfloor heating), often also accomplished using electrical means. The observation of positive association with electricity consumption points towards prevalence of electricity-based system (whether direct or for heating the heat transfer fluid), although we remain cautious in absence of more detailed information. Lastly, we also observe an intuitive finding concerning the positive association between number of TV units or computer screens and electricity consumption. As for the remaining appliances-related parameters, we note that for most part the observed coefficients are intuitive, though not attaining the required statistical significance.

Moving to variables related to year, month and day of the week, we notice that observations made in 2018 reported lower electricity consumption when compared to those made in 2016 and 2017. This might be indicative of a general pro-energy conservation shift among the households. As for the months, we observe a rather non-monotonic pattern, which could reflect a combination of holiday times or prevailing weather conditions (except for the variables controlled for). A more intuitive pattern can be observed for the days of the week, where weekend and adjacent weekdays are characterised with higher consumption as compared to mid-week days. This is likely reflecting higher presence of household members at home during weekend and extended weekends, translated into more extended use of appliances. In terms of the time-of-day effects, late afternoon and evening times are characterised by higher consumption, which is intuitive due to the appliance use and need for lighting. At the same time, late evening and very early morning times have lower consumption as compared to the reference time period. Note also that for controlling purposes, model 3 required introduction of the complete set of time-of-day parameters, including 07:00-20:59, to ensure robustness of the aforementioned PV interaction.

As for the weather parameters, we observe a negative relationship with air temperature, which may indicate an increased need for heating or warm food and beverages. The negative association of electricity demand

[3] The range of time was established by testing two-hourly time-of-day variables and observing their similarity (and thus replacement with a single parameter, which did not result in reduction in the model's fit). Naturally, the late afternoon and early evening times would only be associated with daylight during late spring and early summer months. This effect could be tested with further interactions with months of observation, though in the present context this was not possible due to the sample size.

with the relative humidity may reflect the fact that higher relative humidity requires lower temperature to achieve thermal comfort, possibly leading to a reduced energy demand for heating [48]. At the same time, high humidity accompanied with high temperature may lead to the experience of sweating conditions and thermal discomfort. In fact, this relationship is reflected in the positive association with dew point, which can motivate the use of fans or air conditioners.

The last set of variables reflects differences in electricity consumption depending on the electricity pricing and tariffs. Households with economy and green tariffs report lower electricity consumption on average, as compared to households with standard or other tariffs. Whilst for the green tariff consumers, this could be interpreted as pro-conservation behaviour, the interpretation is less clear for economy tariff consumers. Further interaction of this term, using a larger dataset (given the present focus on activity analysis), could reveal whether the effect holds in general or is simply indicative of data sampling during periods when the peak pricing applies. Whilst we do not observe a significant relationship between electricity demand and standing charge, we note its association with the price per kWh. Specifically, we observe a price elasticity (since logarithm of the price is regressed) of between -.776±0.139 (recall bottom of Table 5 for calculation of the CI). Remarkably, this estimate, despite being based on cross-sectional data, is broadly in line with the estimates provided in the literature [49]. We did not find any effect of household income on elasticity of the demand, despite expectation that more affluent households would have an inelastic demand with respect to price [49]. With a larger sample and more variable pricing that does not rely only on the sample cross-section, we would expect the framework to pick up this effect via suitable interaction terms. In fact, similar investigation using other variables could provide a means of estimating price elasticity for various segments of consumers, stratified by household attributes, device and appliance ownership or time use patterns and also varying across time (time of day, day of week, month). Such knowledge, on the other hand, could assist in formulating novel energy tariffs suitable to particular customer segments' needs while also achieving objectives of the energy system management.

4.2.2 Activities in the household

In terms of the role of activity participation, we distinguish two types of effects: activity being undertaken by the household (by at least one person) and number of participants in that activity from either the household or outside it. The reference point for the activities is a scenario where such activities are not undertaken in the household by any member. To that end, we do not observe statistically significant effects for work, although the obtained parameter suggests a slight uplift. The related activity of studying, on the other hand, is associated with a reduction in consumption. This could indicate the need for creating a suitable milieu for studying, without much use of appliances and disruptions.

We do not observe statistically significant association with reporting sleep, nor the effect of multiple individuals sleeping. This is largely intuitive, as sleep does not tend to involve use of any additional electricity-consuming appliances and takes.

The most interesting set of results concerns home care, personal care and leisure activities. As these activities are reported in high numbers, a more sophisticated analysis of their effects is possible via interaction terms reflecting the different circumstances under which the activities are undertaken. Home care activities are associated with about 9.6% higher electricity consumption, which is even higher for activities undertaken between 15:00 and 16:59, and lower when involving multiple participants. Referring to Appendix 1, it is noteworthy that more solitary examples of such activities include cleaning or cooking, which intuitively are associated with a higher demand for electricity. At the same time, it is also possible to identify more interactive examples, e.g. caring and accompanying, which are naturally less electricity-demanding.

As for personal care activities, the estimated coefficient indicates about 11.3% higher electricity consumption, and a further 6.7% uplift per each employed household member involved in such activities. The effect of employment status may reflect the need for extra effort in washing and formal dressing, associated with the expectations in professional contexts. The uplift is substantially reduced for the evening hours, perhaps reflecting a reduced use of appliances during evening meals. This interpretation is supported by observation that the coefficient associated with number of participants loses its significance between Models 2 and 3. However, the effect of personal care activities is less pronounced between 19:00 and 20:59, which could involve eating dinner and not using other appliances during that time (food preparation is captured under 'Home care', as per Appendix 1).

In general, reporting leisure activities is associated with about 15.7% of uplift in electricity consumption. Interestingly, additional participants in leisure activities tend to reduce the uplift, especially during evening hours. At the same time, undertaking activity between 11:00 and 12:59 is observed to be associated with an uplift in demand. The pattern is likely reflecting more electricity-demanding solitary leisure activities (media, playing games) as opposed to more social activities, involving less use of appliances and more interaction between individuals.

4.3 MARGINAL CHANGE IN ELECTRICITY CONSUMPTION DUE TO THE ACTIVITY UNDERTAKEN IN THE HOUSEHOLD

The final, yet fundamental piece of analysis estimates the marginal change in electricity consumption due to the activity undertaken in the household. This analysis forms the link between ability of the proposed model to infer suitable coefficients and capability of estimating how much participation in activities contributes to household energy (electricity in the current empirical context) demand. In order to ensure robustness of the findings, the analysis is performed only for those activities with a high number of observations, i.e. personal care, home care and leisure, as indicated in Table 2. Moving beyond the present proof-of-concept estimates would certainly warrant collection of a more representative dataset across a larger sample, so that intensities for a wider, possibly more disaggregate set of activities could be obtained reliably.

To obtain such estimates of the marginal change in electricity consumption, we propose the following procedure, based on principles of microsimulation [50]. Firstly, subsamples of observations are obtained for each activity type. For each activity, the number of participants is set to 1 to remove the effect of multiple participants. Subsequently, Model 3 (established as the preferred one earlier in this section) is used to predict the household electricity consumption for the activity-specific subsamples. Subsequently, the consumption is predicted for the same episodes and variable settings except for the activity presence indicator variable (denoted as δ_{ka_t} in Equation 1) which is flipped from 1 to 0. In other words, we assume absence of the activity, ceteris paribus. The model is then used to make predictions of the household electricity consumption. The difference in the predictions provides an estimate of the impact of the activity taking place on the household consumption. Since the predictions are obtained for the episodes during which activities were indeed reported, they are realistic estimates that account for the broader set of circumstances of the households, as captured by other variables in the model. This realism is essential for accurate modelling of demand, e.g. for DSR-type applications. Importantly, the obtained estimates reflect the instantaneous, first-order effects of an activity being undertaken. The procedure does not capture second-order effects, such as changes in the preceding or subsequent activity sequences [17,51,52]. Capturing such effects would require additional activity synthesisation and scheduling components [53,54], which remain beyond scope and capabilities of the present model.

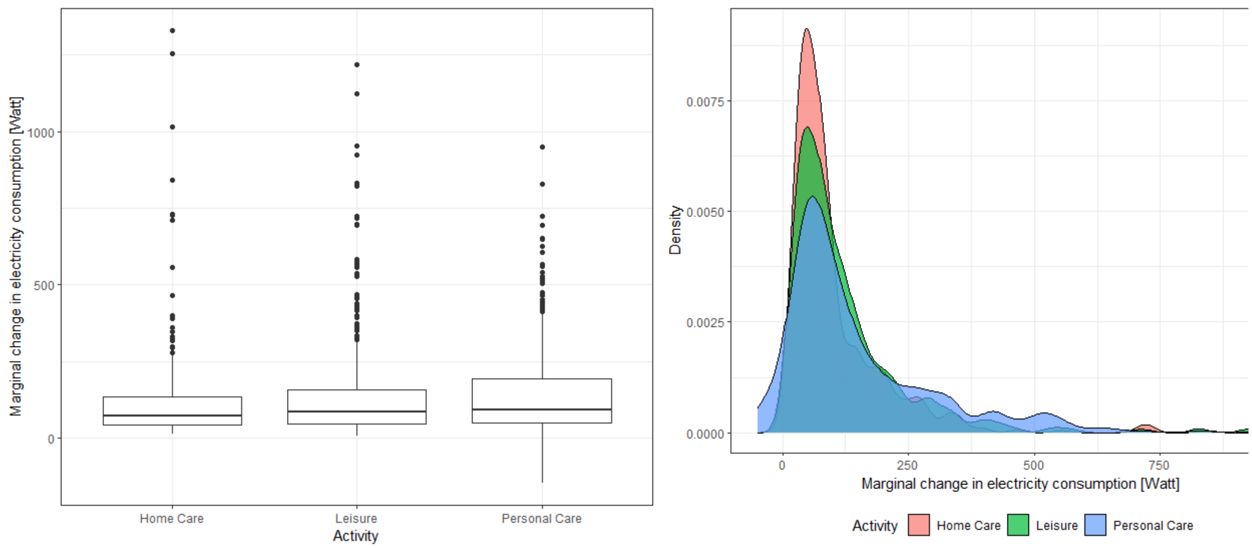

Fig. 4. Estimated marginal change in electricity consumption due to the activity undertaken in the household for home care, leisure and personal care activities (based on Model 3)

The obtained values are presented in Figure 4, in the form of boxplots (entire range of the obtained values) and histograms (censored at 1000 Watt for more effective visualisation). The first observation is that majority of the obtained values for all activities fall between 0 and 250 Watt, as visible in both the boxplots and histograms. This is below the values reported by Diakonova & Grunewald [27,28] in their analysis of the dataset, possibly due to employment of a different methodology which estimated attribution of activity using a 'de-meaned' demand, i.e. with the baseline demand (estimated as the minimum load observed) subtracted. Arguably, given that the present approach allows for such a baseline to vary depending on the contextual factors, the resulting marginal changes in electricity consumption due to the activity undertaken in the household are expected to be lower.

Furthermore, it is also possible to observe marginal change in electricity consumption due to personal care activity to be below zero, i.e. activity presence being associated with a reduced consumption. This is a direct result of the presence of time-of-day interaction variables for personal care activities. In fact, Diakonova and Grunewald [28] made a similar observation where presence of certain activities could be associated with reduced demand for electricity. The novel insights offered by the present approach concerns the ability to reveal when such situations can take place, i.e. during specific times of day. A possible further explanation could indicate reduced use of specific appliances, though further analysis would be required to understand the detailed role of appliance use for such activities. Unfortunately, while the present framework *does* allow for such effects (time-dependent terms $\sum_{d=1}^{D} \beta_d \delta_{kd_t}$ in Equation 1), the available data is insufficient for estimating such effects. More generally, an expanded analysis that could incorporate further interaction terms could arguably reveal more contexts during which the overall semi-elasticity negative. Such insights are valuable as they can reveal activity arrangements that have an associated lower energy consumption. This could point towards strategies that incentivise particular behavioural shifts in activities to achieve the reduction in demand whilst still allowing the activity to be conducted. Naturally, the underlying causal links between activities' contribution to energy consumption and when it is conducted (or indeed with any other factors that result in lower or negative semi-elasticity) would need to be examined. Nevertheless, this points towards a research avenue that could make use of similar data collection protocols alongside collecting data from smart meters and appliances that carry a record of appliance use over time as well as suitable causal-inference methods.

5. CONCLUSIONS AND OUTLOOK

The need for large scale and high-resolution capability of modelling and simulation of energy policies calls for approaches that are grounded in human behaviour and explicitly reflect the activities of consumers. The ability to provide granular insights using an activity-based approach is argued to facilitate the design and implementation of demand management policies, especially with regards to demand side response measures, through understanding of their effects at micro-, meso- and macro-scales. Inevitably, the effectiveness of such modelling and simulation tools ultimately depends on the ability to accurately characterise the agents and their behaviour, including their activities, under different circumstances. To date, efforts looking at translating activity participation into demand for energy have been limited, especially in terms of *simultaneously* capturing contextual variables known to influence electricity consumption, e.g. household composition, residence type or weather, alongside those reflecting a more dynamic aspect of life, i.e. individual presence, activities and use of appliances.

To address this gap, the present paper provides a flexible framework that links the domains of activity-based modelling and the modelling of energy demand. The model, formulated as a log-linear mixed-effects regression, provides a means through which energy consumption data collected alongside time-use and contextual variables yields a set of (semi-) elasticities, in the form of model parameters. Importantly, it is shown that incorporation of considerations related to time use as well as further interaction terms lead to frameworks not only offering additional behavioural insights, but also superior statistical performance. The findings support the value of the proposed approach as an analytical tool for systematically decomposing the drivers of demand, enabling a wide range of assessments such as drivers of consumption resulting from sociodemographic changes, including sensitivity to energy policies amongst certain sociodemographic groups. To that end, it is believed that the present approach can feed into the emerging field of energy epidemiology that indeed calls for 'evidence base […] to identify associations and establish underlying causes behind outcomes and variations in end-use energy demand within the population' [55].

Beyond inferential purposes, the framework can underpin predictions concerning energy consumption of agents (households in the current context) under circumstances reflected by the covariates. This is arguably a key capability required to deliver DSR-like services related to behavioural changes, themselves driven by how activities are conducted. Such an application, given the level of detail and extent of factors that can be reflected by the covariates, can be suitable for a wide range of scenarios. An arguably particularly vivid example concerns analysis of the impacts on energy consumption of large-scale restrictions on out-of-home activities ('lockdowns'). While prior to the COVID-19 pandemic, such large-scale lockdowns have remained very hypothetical scenarios, their materialisation in 2020 points clearly towards the need for an agile toolkit capable of simulating a variety of non-conventional circumstances alongside, for example, drivers of renewable energy generation, i.e. weather conditions. An early attempt at such modelling using the approach proposed in the present paper has been attempted in Trask et al. 2021 [56] and this line of research is expected to continue.

In a similar nominative fashion, virtualisation of lifestyles and the associated shift of activities towards home-based online participation, warrants the development of toolkits that can effectively reflect such shifts, especially in terms of their dependence on attributes of the individuals and their households. This would certainly prove valuable for energy demand management from the point of view of modelling spatio-temporal variations in demand and perhaps role for localised generation and storage, reducing the need for investments in transmission and generation capacity. Such applications are part of the ongoing efforts by the research team.

In conclusion, a few of the limitations of the proposed approach and suggestions for further research warrant outlining. Most importantly, the present model, especially if applied in the reverse manner as a simulation tool, makes an implicit assumption about the causal relationship between the covariates and electricity demand. Whilst the direction of causality in the current analysis is credible (i.e. postulated covariates affecting the consumption, not the other way round), the extent to which *variations* in such covariates would induce changes in the consumption is not guaranteed. In fact, the ability to incorporate findings from experimental studies and field trials, which can demonstrate causal effects much more robustly, as revisions to the estimated (semi-)elasticities in the framework concerns an existing line of research, with findings to be reported in due course.

A recent investigation of bottom-up activity-based energy demand models highlighted the limitations of activity-based energy demand models specifically due to use of national time use diaries as the primary source of data for activities [7]. Our study has also similar limitations. The time use diaries do not differentiate between energy intensive and low energy alternatives of a specific activities (e.g., "food preparation" activity could be preparing a full cooked meal or cutting up vegetables for a salad). Further, such data collection efforts are usually limited to time use diary for a single person for a single day. Nevertheless, the proposed methodology could be expanded accordingly when more detailed data is available. Further, the present analysis reveals the crucial need for a recording protocol that incorporates both start and end times of activities, following the convention of time use analysis elsewhere. In addition, such a record should incorporate the option to report use of devices, again, with start and end times. In a similar manner, collecting detailed information concerning tariff and energy pricing as well as local weather is important in reducing any errors due to imputation of such data from other sources. Importantly, the model in its general formulation (as outlined in Eq.1) can accommodate such richer data.

Furthermore, the current empirical analysis focuses on electricity whilst information concerning consumption of other sources of energy would certainly add to the accuracy of the model. Indeed, it is possible to envision a simultaneous modelling of electricity consumption alongside other energy sources, e.g., gas, heat, which the proposed methodology does allow. Similarly, where local generation and storage capacity is present in the household, further information would be useful concerning its attributes (capacity, installation type), operation as well as motivation for acquisition of such installation. A key variable also concerns energy efficiency of the house, which was absent from the current data and therefore likely manifested indirectly in other variables (e.g. related to temperature and heating-related appliances) and error term. Arguably, this information would allow a more integrated modelling of the gross energy demand of the household as opposed to net demand (or excess supply), considering the local generation and storage capacity. Lastly, the current empirical analysis is based on a restricted sample not necessarily representative of the general population and placed in a particular climate zone. Arguably, a more representative sample, e.g., collected as part of regular time use data collection surveys or as part of a regular operators' effort to monitor preferences and behaviours, possibly leveraging the increasing use of smart meters may offer future opportunities for analysis and simulation, more representative of the entire country. In addition, larger samples would allow further interaction terms to be introduced and tested in the model, reflecting arbitrarily sophisticated interactions between energy demand and activity type (possibly with a more granular categorisation, such as the fine UK Time Use Survey categorisation presented in Appendix 1), its timing and attributes of the participating individuals. Similarly, cross-national comparisons following the proposed framework could yield more insights into national-level factors, such as energy policy environment, culture or climate, acknowledging that links between activities and energy consumption may vary across such dimensions.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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APPENDIX 1: ACTIVITY CATEGORISATION

The table (Table A1) below presents mapping between the UK Time Use Survey (UK TUS) 2014-15 coding [57] as used in the Project METER [27,28] and one used in the present study. Note that organisational work, shopping, trips and unknown activities were not present in the model as no observations for such activities with home location were observed.

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	**Activity code**
Work	Unspecified main job	1100
Work	Working time in main job	1110
Work	Coffee and other breaks in main job	1120
Work	Working time in second job	1210
Work	Coffee and other breaks in second job	1220
Work	Unspecified activities related to employment	1300
Work	Other specified activities related to employment	1390
Work	Activities related to job seeking	1391
Work	Other specified activities related to employment	1399
Sleep	Sleep	110
Home care	Unspecified household and family care	3000
Home care	Unspecified food management	3100
Home care	Food preparation and baking	3110
Home care	Dish washing	3130
Home care	Preserving	3140
Home care	Other specified food management	3190
Home care	Unspecified household upkeep	3200
Home care	Cleaning dwelling	3210
Home care	Cleaning yard	3220
Home care	Heating and water	3230
Home care	Arranging household goods and materials	3240
Home care	Disposal of waste	3250
Home care	Other or unspecified household upkeep	3290
Home care	Unspecified making and care for textiles	3300
Home care	Laundry	3310
Home care	Ironing	3320
Home care	Handicraft and producing textiles	3330
Home care	Other specified making and care for textiles	3390
Home care	Gardening	3410
Home care	Tending domestic animals	3420
Home care	Caring for pets	3430
Home care	Walking the dog	3440
Home care	Other specified gardening and pet care	3490
Home care	Unspecified construction and repairs	3500

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	**Activity code**
Home care	House construction and renovation	3510
Home care	Repairs of dwelling	3520
Home care	Making repairing and maintaining equipment	3530
Home care	Woodcraft metalcraft sculpture and pottery	3531
Home care	Other specified making repairing and maintaining equipment	3539
Home care	Vehicle maintenance	3540
Home care	Other specified construction and repairs	3590
Home care	Commercial and administrative services	3620
Home care	Household management not using the internet	3710
Home care	Unspecified household management using the internet	3720
Home care	Banking and bill paying via the internet	3727
Home care	Other specified household management using the internet	3729
Home care	Unspecified childcare	3800
Home care	Unspecified physical care & supervision of a child	3810
Home care	Feeding the child	3811
Home care	Other and unspecified physical care & supervision of a child	3819
Home care	Teaching the child	3820
Home care	Reading playing and talking with child	3830
Home care	Accompanying child	3840
Home care	Other or unspecified childcare	3890
Home care	Unspecified help to a non-dependent e.g. injured adult household member	3910
Home care	Physical care of a non-dependent e.g. injured adult household member	3911
Home care	Accompanying a non-dependent adult household member e.g. to hospital	3914
Home care	Other specified help to a non-dependent adult household member	3919
Home care	Unspecified help to a dependent adult household member	3920
Home care	Physical care of a dependent adult household member e.g. Alzheimic parent	3921
Home care	Accompanying a dependent adult household member e.g. Alzheimic	3924
Home care	Other specified help to a dependent adult household member	3929
Home care	Unspecified informal help to other households	4200
Home care	Food management as help to other households	4210
Home care	Household upkeep as help to other households	4220
Home care	Gardening and pet care as help to other households	4230
Home care	Construction and repairs as help to other households	4240
Home care	Help to other households in employment and farming	4260
Home care	Unspecified childcare as help to other households	4270
Home care	Physical care and supervision of child as help to other household	4271
Home care	Teaching non-coresident child	4272

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	**Activity code**
Home care	Reading playing & talking to non-coresident child	4273
Home care	Accompanying non-coresident child	4274
Home care	Physical care and supervision of own child as help to other household	4275
Home care	Reading playing & talking to own non-coresident child	4277
Home care	Accompanying own non-coresident child	4278
Home care	Other specified childcare as help to other household	4279
Home care	Unspecified help to an adult of another household	4280
Home care	Physical care and supervision of an adult as help to another household	4281
Home care	Accompanying an adult as help to another household	4282
Home care	Other specified help to an adult member of another household	4283
Home care	Other specified informal help to another household	4289
Home care	Other specified informal help	4290
Home care	Filling in the time use diary	9950
Personal care	Unspecified personal care	0
Personal care	Sick in bed	120
Personal care	Eating	210
Personal care	Unspecified other personal care	300
Personal care	Wash and dress	310
Personal care	Other specified personal care	390
Personal care	Lunch break	1310
Personal care	Personal services	3630
Study	Unspecified study school or university	2000
Study	Unspecified activities related to school or university	2100
Study	Classes and lectures	2110
Study	Homework	2120
Study	Other specified activities related to school or university	2190
Study	Free time study	2210
Leisure	Arts and hobbies	71
Leisure	TV and video	82
Leisure	In bed not asleep	111
Leisure	Unspecified social life and entertainment	5000
Leisure	Unspecified social life	5100
Leisure	Socialising with family	5110
Leisure	Visiting and receiving visitors	5120
Leisure	Celebrations	5130
Leisure	Telephone conversation	5140
Leisure	Other specified social life	5190
Leisure	Unspecified entertainment and culture	5200
Leisure	Cinema	5210

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	**Activity code**
Leisure	Unspecified theatre or concerts	5220
Leisure	Plays musicals or pantomimes	5221
Leisure	Opera operetta or light opera	5222
Leisure	Concerts or other performances of classical music	5223
Leisure	Live music other than classical concerts, opera, and musicals	5224
Leisure	Dance performances	5225
Leisure	Other specified theatre or concerts	5229
Leisure	Art exhibitions and museums	5230
Leisure	Unspecified library	5240
Leisure	Borrowing books records audiotapes videotapes CDs VDs etc. from a library	5241
Leisure	Reference to books and other library materials within a library	5242
Leisure	Using internet in the library	5243
Leisure	Using computers in the library other than internet use	5244
Leisure	Reading newspapers in a library	5245
Leisure	Other specified library activities	5249
Leisure	Sports events	5250
Leisure	Other specified entertainment and culture	5290
Leisure	Visiting a historical site	5291
Leisure	Visiting a wildlife site	5292
Leisure	Visiting a botanical site	5293
Leisure	Visiting a leisure park	5294
Leisure	Visiting an urban park playground designated play area	5295
Leisure	Other or unspecified entertainment or culture	5299
Leisure	Resting - Time out	5310
Leisure	Unspecified sports and outdoor activities	6000
Leisure	Unspecified physical exercise	6100
Leisure	Walking and hiking	6110
Leisure	Taking a walk or hike that lasts at least miles or 1 hour	6111
Leisure	Other walk or hike	6119
Leisure	Jogging and running	6120
Leisure	Biking skiing and skating	6130
Leisure	Biking	6131
Leisure	Skiing or skating	6132
Leisure	Unspecified ball games	6140
Leisure	Indoor pairs or doubles games	6141
Leisure	Indoor team games	6142
Leisure	Outdoor pairs or doubles games	6143
Leisure	Outdoor team games	6144
Leisure	Other specified ball games	6149

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	Activity code
Leisure	Gymnastics	6150
Leisure	Fitness	6160
Leisure	Unspecified water sports	6170
Leisure	Swimming	6171
Leisure	Other specified water sports	6179
Leisure	Other specified physical exercise	6190
Leisure	Unspecified productive exercise	6200
Leisure	Hunting and fishing	6210
Leisure	Picking berries mushroom and herbs	6220
Leisure	Other specified productive exercise	6290
Leisure	Unspecified sports related activities	6310
Leisure	Activities related to sports	6311
Leisure	Activities related to productive exercise	6312
Leisure	Unspecified hobbies games and computing	7000
Leisure	Unspecified arts	7100
Leisure	Unspecified visual arts	7110
Leisure	Painting drawing or other graphic arts	7111
Leisure	Making videos taking photographs or related photographic activities	7112
Leisure	Other specified visual arts	7119
Leisure	Unspecified performing arts	7120
Leisure	Singing or other musical activities	7121
Leisure	Other specified performing arts	7129
Leisure	Literary arts	7130
Leisure	Other specified arts	7140
Leisure	Unspecified hobbies	7150
Leisure	Collecting	7160
Leisure	Correspondence	7170
Leisure	Other specified or unspecified arts and hobbies	7190
Leisure	Computing - programming	7220
Leisure	Unspecified information by computing	7230
Leisure	Information searching on the internet	7231
Leisure	Other specified information by computing	7239
Leisure	Unspecified communication by computer	7240
Leisure	Communication on the internet	7241
Leisure	Other specified communication by computing	7249
Leisure	Unspecified other computing	7250
Leisure	Skype or other video call	7251
Leisure	Other specified computing	7259
Leisure	Unspecified games	7300

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	Activity code
Leisure	Solo games and play	7310
Leisure	Unspecified games and play with others	7320
Leisure	Billiards pool snooker or petanque	7321
Leisure	Chess and bridge	7322
Leisure	Other specified parlour games and play	7329
Leisure	Computer games	7330
Leisure	Gambling	7340
Leisure	Other specified games	7390
Leisure	Unspecified mass media	8000
Leisure	Unspecified reading	8100
Leisure	Reading periodicals	8110
Leisure	Reading books	8120
Leisure	Other specified reading	8190
Leisure	Unspecified TV video or DVD watching	8210
Leisure	Watching a film on TV	8211
Leisure	Watching sport on TV	8212
Leisure	Other specified TV watching	8219
Leisure	Unspecified video watching	8220
Leisure	Watching a film on video	8221
Leisure	Watching sport on video	8222
Leisure	Other specified video watching	8229
Leisure	Unspecified listening to radio and music	8300
Leisure	Unspecified radio listening	8310
Leisure	Listening to music on the radio	8311
Leisure	Listening to sport on the radio	8312
Leisure	Other specified radio listening	8319
Leisure	Listening to recordings	8320
Leisure	Travel for day trip/just walk	9820
Organisational work	Unspecified volunteer work and meetings	4000
Organisational work	Unspecified organisational work	4100
Organisational work	Work for an organisation	4110
Organisational work	Volunteer work through an organisation	4120
Organisational work	Other specified organisational work	4190
Organisational work	Unspecified participatory activities	4300
Organisational work	Meetings	4310
Organisational work	Religious activities	4320
Organisational work	Other specified participatory activities	4390
Shopping	Unspecified shopping and services	3600
Shopping	Unspecified shopping	3610
Shopping	Shopping mainly for food	3611

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	Activity code
Shopping	Shopping mainly for clothing	3612
Shopping	Shopping mainly related to accommodation	3613
Shopping	Shopping or browsing at car boot sales or antique fairs	3614
Shopping	Window shopping or other shopping as leisure	3615
Shopping	Other specified shopping	3619
Shopping	Other specified shopping and services	3690
Shopping	Shopping for and ordering clothing via the internet	3713
Shopping	Shopping for and ordering unspecified goods and services via the internet	3721
Shopping	Shopping for and ordering food via the internet	3722
Shopping	Shopping for and ordering goods and services related to accommodation via the internet	3724
Shopping	Shopping for and ordering mass media via the internet	3725
Shopping	Shopping for and ordering entertainment via the internet	3726
Shopping	Shopping and services as help to other households	4250
Trips	Travel related to unspecified time use	9000
Trips	Travel related to personal business	9010
Trips	Travel to/from work	9100
Trips	Travel in the course of work	9110
Trips	Travel to work from home and back only	9120
Trips	Travel to work from a place other than home	9130
Trips	Travel related to education	9210
Trips	Travel escorting to/ from education	9230
Trips	Travel related to household care	9310
Trips	Travel related to shopping	9360
Trips	Travel related to services	9370
Trips	Travel escorting a child other than education	9380
Trips	Travel escorting an adult other than education	9390
Trips	Travel related to organisational work	9400
Trips	Travel related to voluntary work and meetings	9410
Trips	Travel related to informal help to other households	9420
Trips	Travel related to religious activities	9430
Trips	Travel related to participatory activities other than religious activities	9440
Trips	Travel to visit friends/relatives in their homes not respondents household	9500
Trips	Travel related to other social activities	9510
Trips	Travel related to entertainment and culture	9520
Trips	Travel related to other leisure	9600
Trips	Travel related to physical exercise	9610
Trips	Travel related to hunting & fishing	9620
Trips	Travel related to productive exercise other than hunting & fishing	9630

Table A1. Mapping between the current activity coding and UK TUS 2014-15

Current study code (activity category)	UK TUS 2014-15 and Project METER	
	Activity description	**Activity code**
Trips	Travel related to gambling	9710
Trips	Travel related to hobbies other than gambling	9720
Trips	Travel related to changing locality	9800
Trips	Travel to holiday base	9810
Trips	Other specified travel	9890
Unknown	No main activity no idea what it might be	9960
Unknown	No main activity some idea what it might be	9970
Unknown	Illegible activity	9980
Unknown	Unspecified time use	9990
Unknown	Not applicable	9991
Unknown	Queryable	9999