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Welcome

1:30	**Arrivals and refreshments**
2:00	**Welcome and opening comments** - Daron Walker, DESNZ
2:05	**Summary of SERL major impacts** - Simon Elam, University College London
2:20	**Metrics of building performance (model validation, performance gap and in-use metrics)**
	- Matt Li, Loughborough University
	- David Johnston, Leeds Beckett University
	- Jessica Few, University College London
3:00	**Diurnal/cyclical variation in energy use (profiles, cluster analysis)**
	- Tom Rushby, University of Southampton
	- Martin Pullinger, University College London
3:30	Break
3:45	**Regional energy use (Welsh/Scottish/regional results)**
	- Martin Pullinger, UCL + University of Edinburgh
	- Simon Lannon, University of Cardiff
4:15	**Policy evaluation & counterfactual - (SENS, GHG) -** Eoghan McKenna, University College London
4:40	**Building on SERL – the Energy Demand Observatory and Laboratory (EDOL) -** Tadj Oreszczyn, UCL
4:55	**Drinks/nibbles**

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The Smart Energy Research Lab: A longitudinal energy data resource for socio-technical research

Simon Elam, Principal Research Fellow, University College London

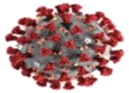
Director of the Smart Energy Research Lab

BEHAVE conference, November 2023

Smart Energy Research Lab (SERL) Project Overview

- **Primary objective: to deliver a unique energy data resource to the research community.**
  - Fair to say that we have successfully delivered on this objective
  - Core component is the SERL Observatory panel: 13,000 GB households
- As well as an innovative research programme utilising SERL data

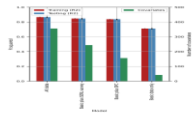
Covid-19 impact on energy consumption



EPC analysis

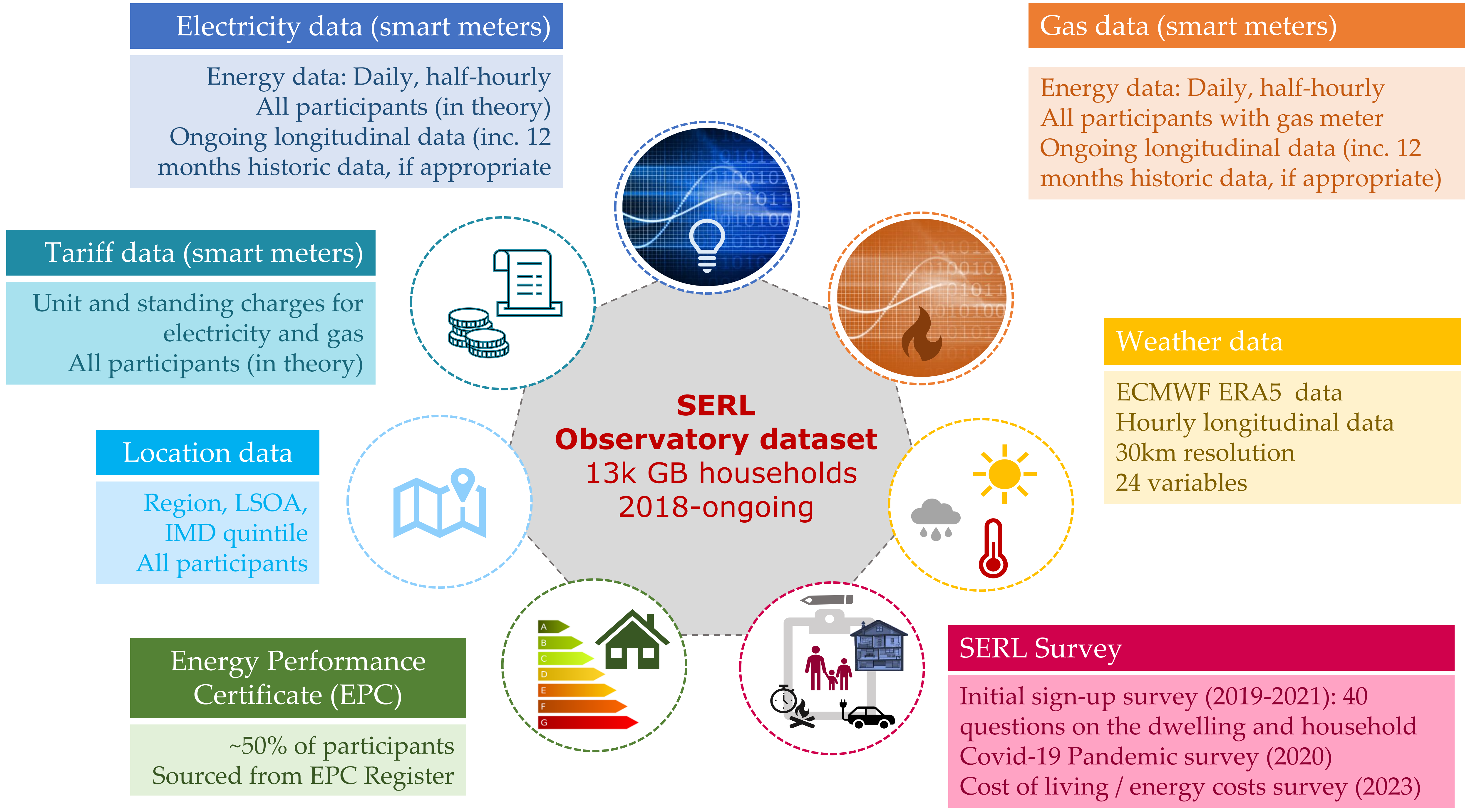
SERL Stats report

Explaining energy demand



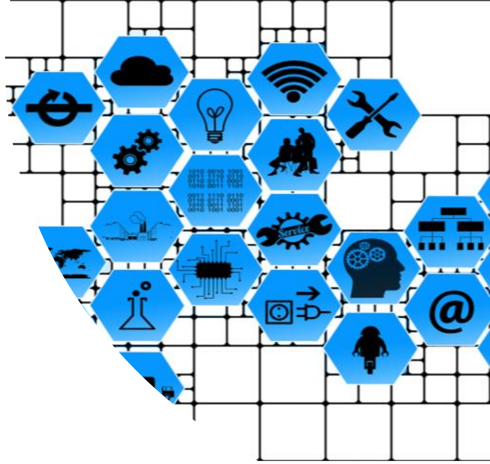
Understanding habitual energy consumption

Identifying fuel poverty



Electricity data (smart meters)
Energy data: Daily, half-hourly
All participants (in theory)
Ongoing longitudinal data (inc. 12 months historic data, if appropriate
Gas data (smart meters)
Energy data: Daily, half-hourly
All participants with gas meter
Ongoing longitudinal data (inc. 12 months historic data, if appropriate)
Tariff data (smart meters)
Unit and standing charges for electricity and gas
All participants (in theory)
Weather data
ECMWF ERA5 data
Hourly longitudinal data
30km resolution
24 variables
SERL
Observatory dataset
13k GB households
2018-ongoing
Location data
Region, LSOA, IMD quintile
All participants
A
B
C
D
E
F
G
Energy Performance Certificate (EPC)
~50% of participants
Sourced from EPC Register
SERL Survey
Initial sign-up survey (2019-2021): 40 questions on the dwelling and household
Covid-19 Pandemic survey (2020)
Cost of living / energy costs survey (2023)

Data Curation/Provisioning – Enabling Research



Secure Observatory dataset

- available via UKDS – SN 8666
- Regular updates (3-6 months)
- Controlled dataset: accredited researchers, approved projects, secure lab
- Robust data Quality Assurance before release
  - Data QA report, data quality flags/scores, data cleaning, derived variables

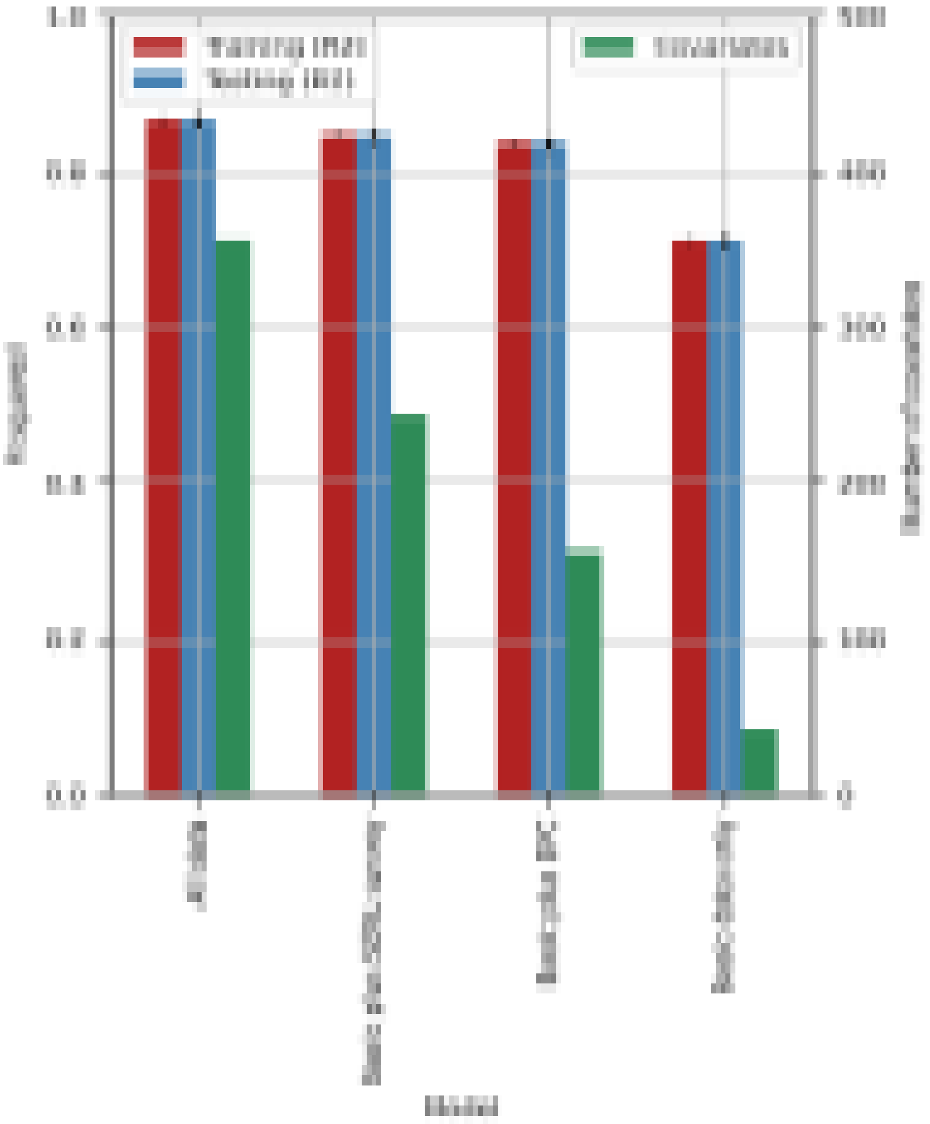
SERL Stats Report

- available via https://serl.ac.uk/key-documents/reports/
- Accompanying Statistical datasets:
  - Granular statistical dataset (110k rows) – Available via UKDS – SN 8963
  - Statistical tables (MS Excel file) – accessible via UCL Research Data Repository
- Volume 2 in December 2023

SERL Works!

- **Excellent explanatory power** – when investigating energy demand using SERL Observatory data and a bottom-up statistical model
- **SERL Observatory data explains between 63% and 80% of the variation in daily household energy consumption (**Adjusted R2 calculated using cross-validation testing errors)
- Roughly **twice the power of other studies/datasets**
  - which report adjusted R2 of 0.29–0.44 for daily demand

- Analyses led by Eoghan McKenna. Paper:[10.1016/j.enbuild.2022.111845](https://doi.org/10.1016/j.enbuild.2022.111845)



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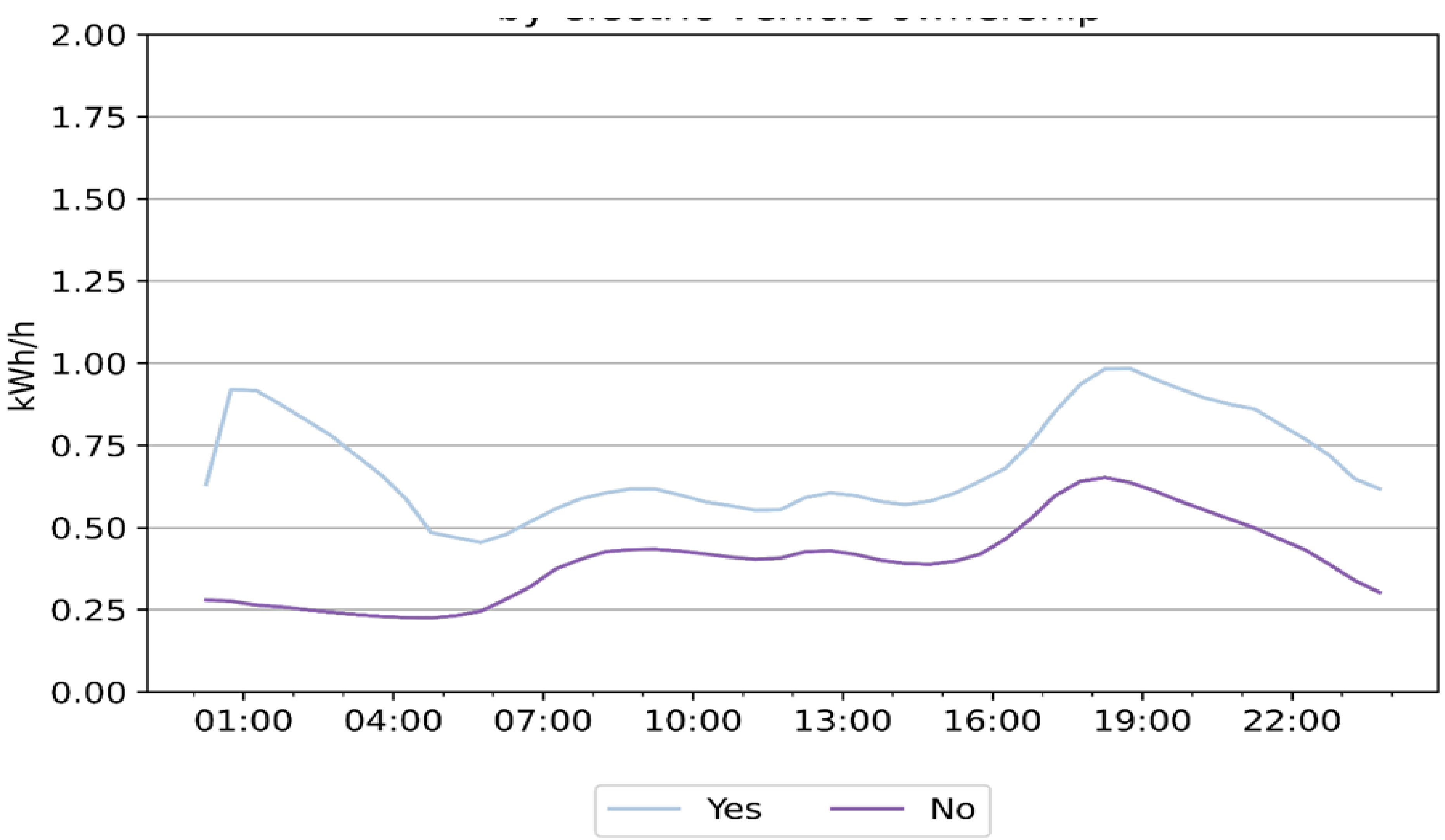
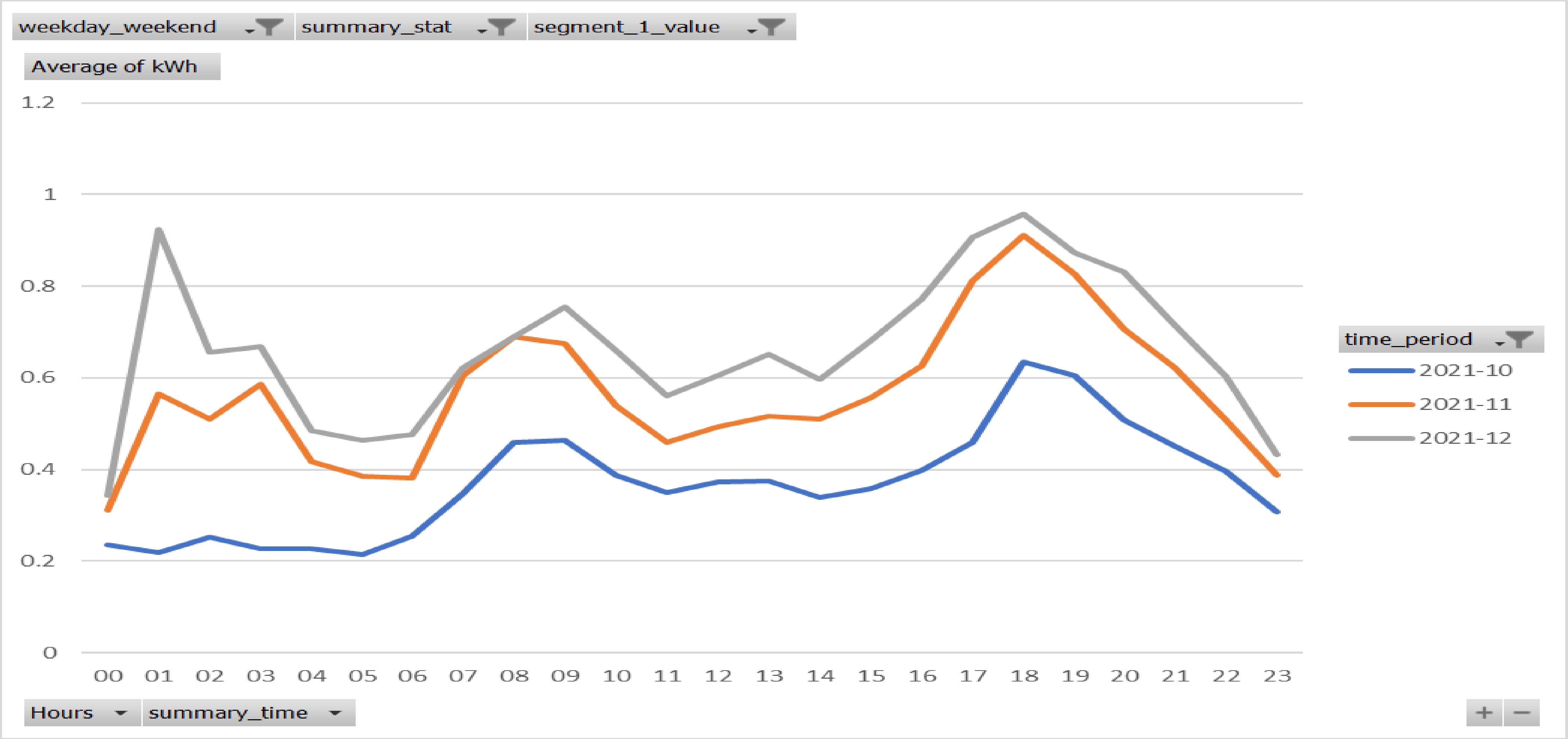
SERL Works - SERL Stats Report: Households with Electric Vehicles



SERL Works: Electrically heated homes



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SERL – Research Utilisation

Projects using controlled Observatory data: 32 (24 live, 8 completed)

- SERL-funded Research Programme: **9**
- Non-SERL (external): **23**
- Researchers: 64 (+19 pending)
- Organisations: 26
- Academic papers: 14
- Industry/Government reports: 4

Laboratory projects: 5

- SENS Trials, GHGS Evaluation, GHGS SMETER, EHS, SHREWD
- Reports: 4

SERL Stats Report

- **Report (Vol. 1): 2935 downloads across 61 countries**
- **Statistical tables: 1693** views; 531 downloads
- **Granular dataset (via UKDS):** 39 access requests across 23 projects; 16 orgs (inc. Office of PM; Cabinet Office).

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Impact highlights (govt/industry reports)

SERL Observatory

- **Project Venice – Impact of the Cost-of-Living Crisis on Domestic Energy Consumption:** Frontier Economics and UCL (2023)
- **Project VENICE: The impact of the pandemic on electricity consumption:** Frontier Economics and UCL (2023)
- **SERL Energy Monitoring for DESNZ** - energy tariffs, expenditure, and elasticity (2023, not yet public)

SERL Laboratories

- **Green Homes Grant Scheme** final report, **GHGS SMETER** (2023) - supported by SERL data and analysis
- **Smart Energy Savings (SENS) trials** (2023) report - supported by SERL data and analysis

Broad Impact

- **Independent Review of Net Zero** (Skidmore, Jan 23) - several references to SERL data
- **'Delivering a Digitalised Energy System'** (Jan 22) – Energy Digitalisation Taskforce calls for extension of SERL
- **Digitalising our energy system for net zero: Strategy and Action Plan** (Jul 21) – SERL highlighted as example of public interest research with smart meter data
- **Smart Meter Public Interest Advisory Group (Final Report)** - calls for extension of SERL

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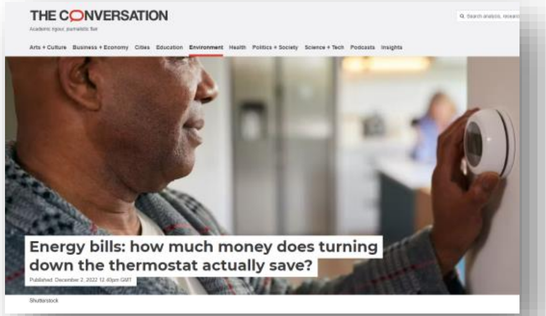
Impact highlights (media & other)

Misc.

- **Smart Future of Healthcare Report** (Nov 2020): informed by SERL data and research
- Daily Telegraph (Apr 22) **'Homes given poor energy ratings on the basis of faulty modelling'** based on SERL EPC work.
- **Energy bills: how much money does turning down the thermostat actually save**? (Dec 22) The Conversation. Over 30k reads.
- **Private Eye magazine references to SERL EPC work** (Jun, Aug 22).
- **'Smart Energy, smart buildings, smart health'** (Aug 21) COP26 UCL 'explainer'



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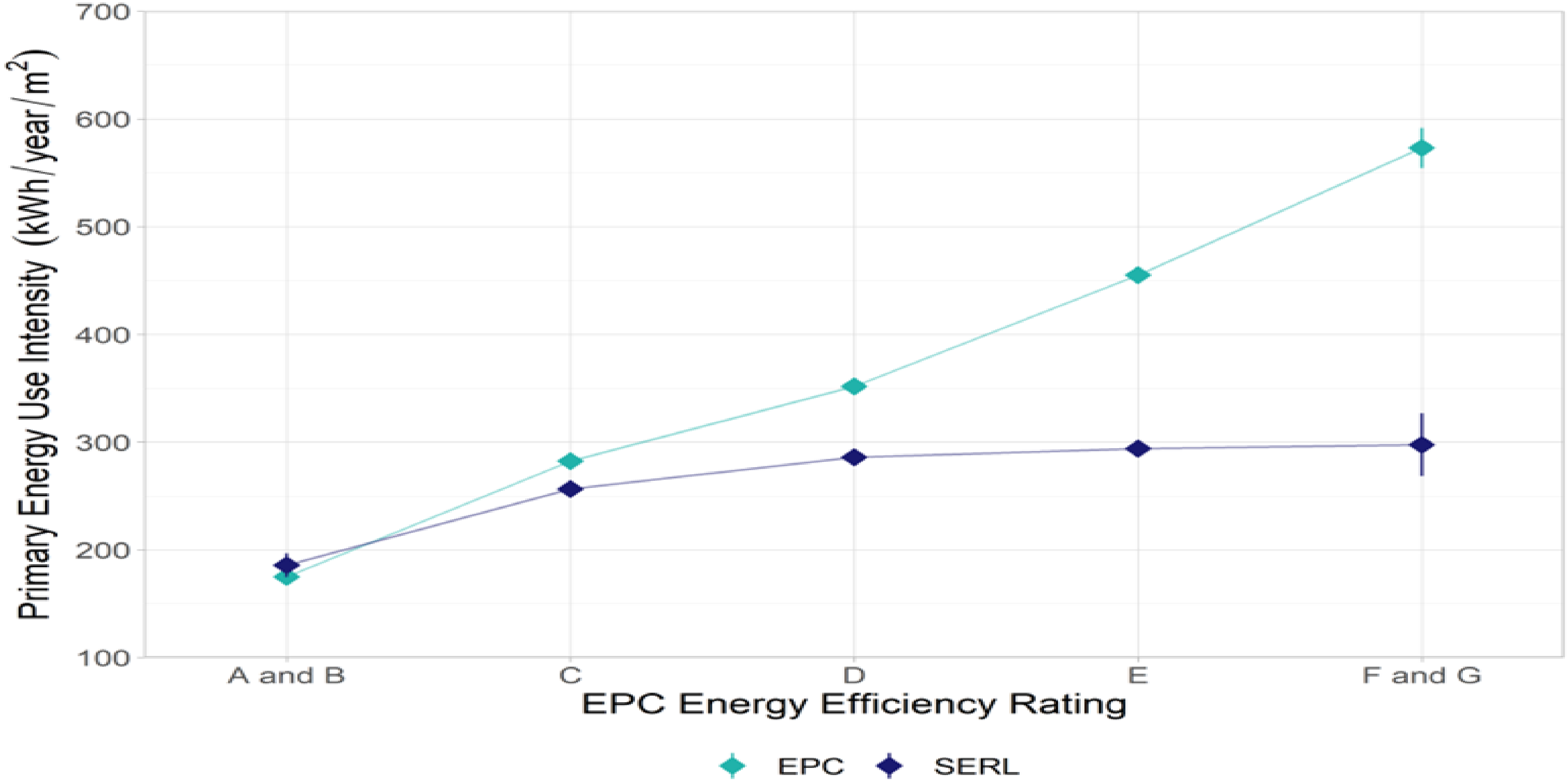
SERL Research outputs



SERL EPC Paper - EPCs overpredict energy use in C to G properties, and over predict the change between bands

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SERL Research outputs

Impact of increasing energy costs in UK in 2022/23 – Behavioural response – Space Heating

42%

39%

52%

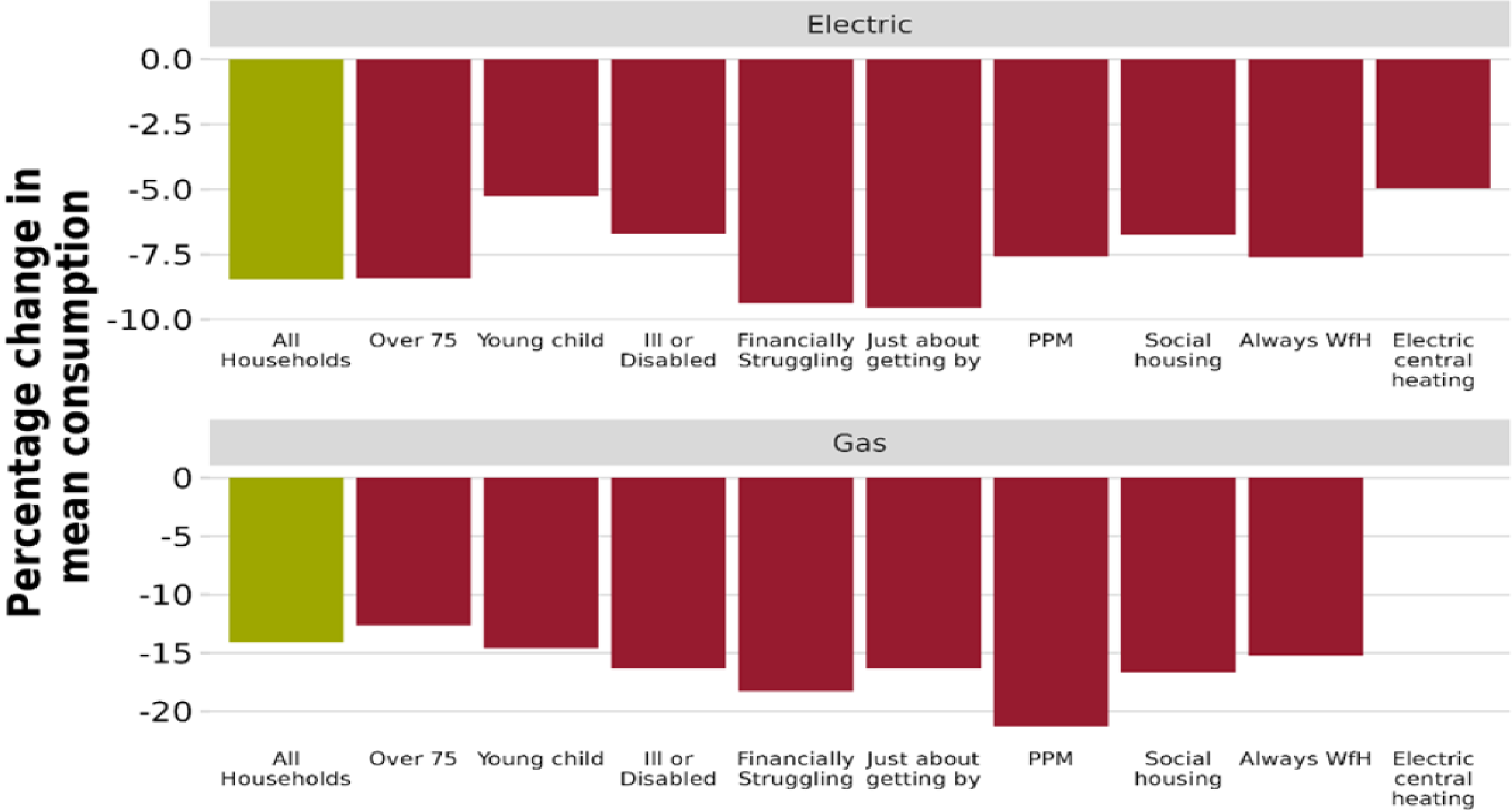
35%

- reduced the flow temperature of their boiler.
- heated for fewer hours than in previous winters.
- left some spaces unheated compared to 35% previously.

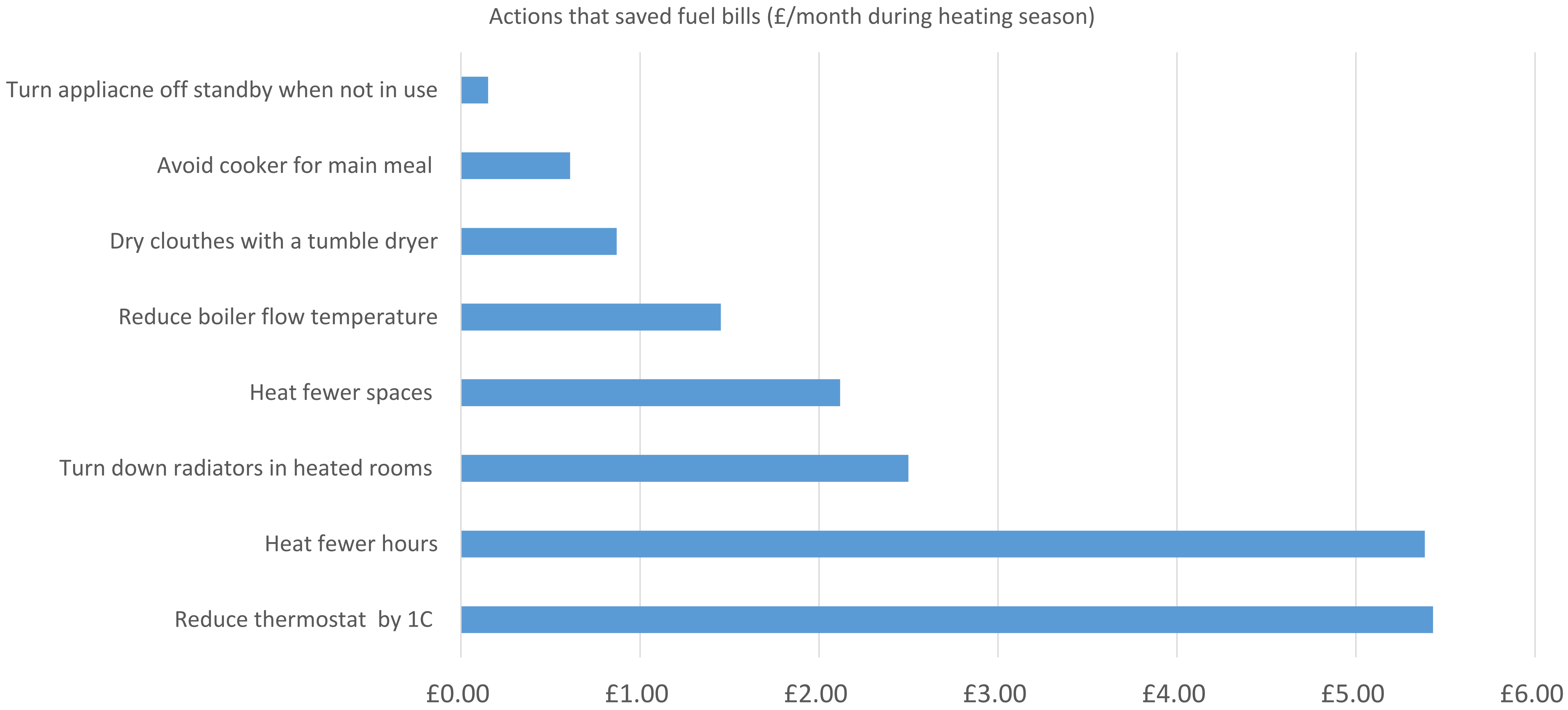
Analyses led by Gesche Huebner, research funded by CREDS. Paper: https://osf.io/preprints/socarxiv/984yh/

SERL Research outputs

Impact of increasing energy costs in UK in 2022/23 – Energy consumption by household type



SERL Research outputs



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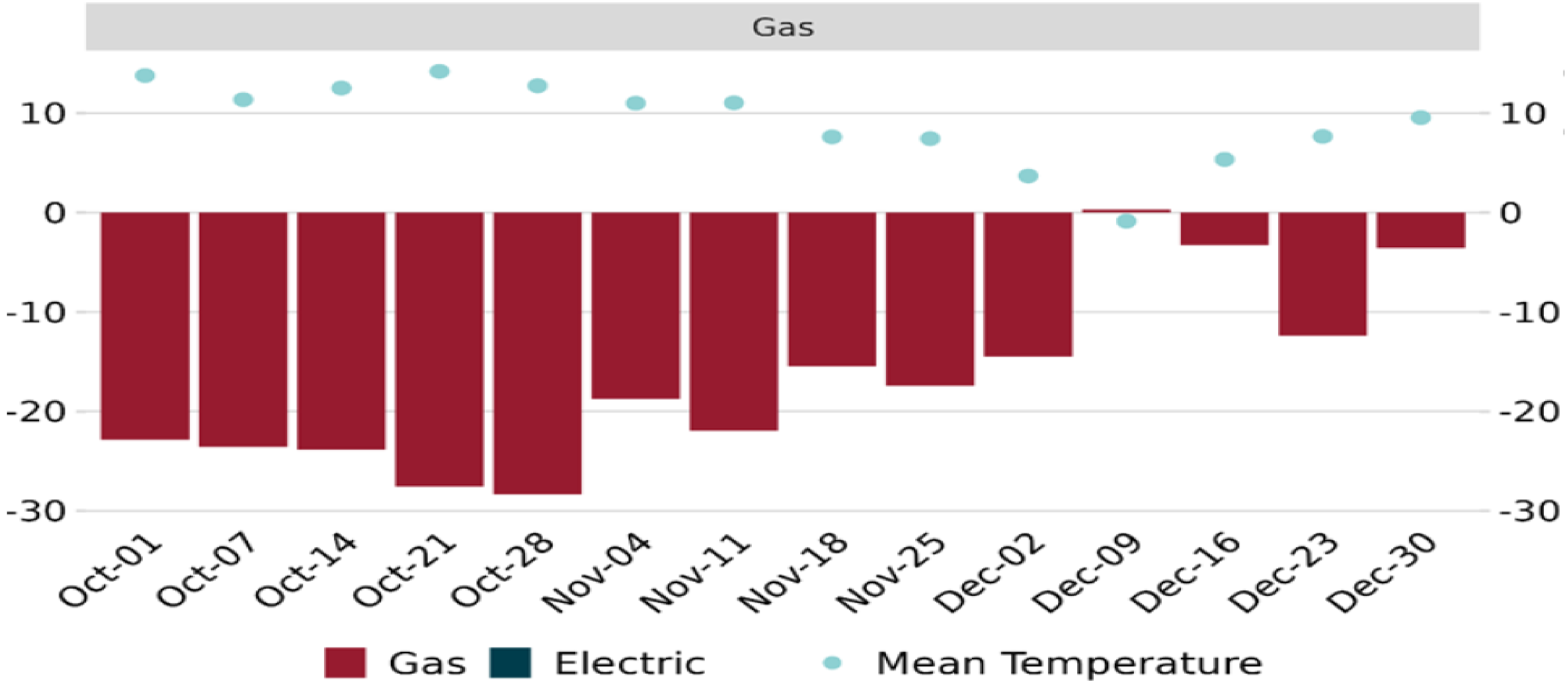
SERL Research outputs

Impact of increasing energy costs in UK in 2022/23 – impact of weather by week



Analyses led by Frontier Economics.
Report: https://www.nationalgrid.co.uk/downloads-view-reciteme/646526

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Impact highlights (academic papers 1)

PRE-PRINT: Zapata-Webborn, E., Hanmer, C., Oreszczyn, T., Huebner, G., McKenna, E., Few, J., Elam, S., Pullinger, M., Cheshire, C., Friel, D., Masters, H., Whittaker, A. (2023) **Winter demand falls as fuel bills rise: Understanding the energy impacts of the cost-of-living crisis on British households (87 downloads, 174 views)**

PRE-PRINT: Huebner, G., Hanmer, C., Zapata-Webborn, E., Pullinger, M., McKenna, E., Few, J., Elam, S., Oreszczyn, T. (2023) **Self-reported energy use behaviour changed significantly during the cost-of-living crisis in winter 2022/23: Insights from cross-sectional and longitudinal surveys in Great Britain (111 views, 29 downloads)**

PRE-PRINT: Pullinger, M., Zapata-Webborn, E., Kilgour, J., Elam, S., Few, J., Goddard, N., Hanmer, C., McKenna, E., Oreszczyn, T., Webb, L. (2023) **Capturing variation in daily energy demand profiles over time with cluster analysis in British homes (September 2019 – August 2022) (79 views, 44 downloads)**

Zapata-Webborn, E., Pullinger, M., McKenna, E., Cheshire, C., Masters. H., Whittaker, A., Few, J., Elam, S., Oreszczyn, T. (2023) **The short- and long-term impacts of COVID-19 on household energy consumption in England and Wales (125 Downloads, 287 views)**

Few, J., Manouseli, D., McKenna, E., Pullinger, M., Zapata-Webborn, E., Elam, S., Shipworth, D. & Oreszczyn, T. (2023) **The over-prediction of energy use by EPCs in Great Britain: A comparison of EPC-modelled and metered primary energy use intensity.** Energy and Buildings. Vol 288. **(5 citations, 4 policy citations ; 61 downloads)**

McKenna, E.J., Few, J., Webborn, E., Anderson, B., Elam, S., Shipworth, D., Cooper, A., Pullinger, M., Oreszczyn, T. (2022) **Explaining daily energy demand in British housing using linked smart meter and socio-technical data in a bottom-up statistical model**, Energy and Buildings. **(14 citations; 51 downloads)**

Impact highlights (academic papers 2)

Anderson B., James P. (2021). **Covid-19 lockdown: impacts on GB electricity demand and CO2 emissions**. Buildings and Cities. (**1133 views, 140 downloads, 4 citations**)

Huebner, G. M., Watson, N. E., Direk, K., McKenna, E., Webborn, E., Hollick, F., . . . Oreszczyn, T. (2021). **Survey study on energy use in UK homes during Covid-19**. Buildings and Cities, 2(1), 952-969. (**1159, views, 7 citations; 145 downloads**)

Webborn, E.. Few, J., McKenna, E., Elam, S., Pullinger, M., Anderson, B., Shipworth, D., Oreszczyn, T. (2021) **The SERL Observatory Dataset: Longitudinal Smart Meter Electricity and Gas Data, Survey, EPC and Climate Data for Over 13,000 GB Households**. Energies 14 (21) (**3170 views, 5 citations**; **93 downloads**)

Webborn, E., McKenna, E. J., Elam, S., Anderson, B., Cooper, A., & Oreszczyn, T. (2021) **Increasing response rates and improving research design: Learnings from the Smart Energy Research Lab in the United Kingdom. Energy Research & Social Science (83**). ISSN 2214-6296 (**2 citations**; **27 downloads**)

Crawley J., McKenna E., Gori, V., Oreszczyn, T. (2020). **Creating Domestic Building Thermal Performance Ratings Using Smart Meter Data**. Buildings and Cities, 1(1), pp. 1-13. (1109 views, 216 downloads, 7 citations)

Webborn, E. & Oreszczyn, T. (2019**) Champion the energy data revolution**. Nature Energy Journal. (**959 accesses, 12 citatations**)

Webborn, E., Elam, S., McKenna, E., Oreszczyn, T. (2019) **Utilising smart meter data for research and innovation in the UK.** In: Proceedings of ECEEE 2019 Summer Study on energy efficiency. (pp. 1387-1396). ECEEE: Belambra Presqu'île de Giens, France. (**630 downloads**)

McKenna E., Webborn E., Leicester P., Elam S. (2019). **Analysis of international residential solar PV self-consumption**. ECEEE 2019 Summer Study on energy efficiency. ECEEE. (**427 downloads**; **12 citations**

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Metrics of building performance (model validation, performance gap and in-use metrics)

Matt Li, Loughborough University

David Johnston, Leeds Beckett University

Jessica Few, University College London

Domestic operational rating (DOR): development, programming and testing

Matt Li & Kevin Lomas
Building Energy Research Group, Loughborough University

2023-Dec-06

Loughborough University

Overview

- Project centred around development, programming & testing of a Domestic Operational Rating (DOR) methodology.

- The DOR methodology, first presented in 2019[1], uses smart meter data to generate metrics describing the energy performance of UK homes.

- Intended to complement Energy Performance Certificate ratings produced by the UK Standard Assessment Procedure (SAP).

- Initially developed using data gathered in 114 privately owned, semi-detached, UK East Midlands homes, all with gas central heating.

1. Lomas et al., 2019. *A domestic operational rating for UK homes: Concept, formulation and application*. Energy & Buildings 201, 90-117.

DOR methodology – a primer

As per 2019 method statement[1]:

- For a given dwelling, DOR uses monitored energy demand & weather data to calculate annual totals for:
  - Energy demand (kWh/m^2)
  - Greenhouse gas (GHG) emissions ($kgCO_2e/m^2$)
  - Energy cost (GBP/m^2)
- Ratings for each then produced by comparison against benchmark values (derived from national statistics).
- Energy demand is weather corrected using a degree-days approach.
- GHG emissions and energy costs calculated from energy demand, using assumed emissions factors & fuel costs.

1. Lomas et al., 2019. *A domestic operational rating for UK homes: Concept, formulation and application*. Energy & Buildings 201, 90-117.

DOR development

Access to the SERL dataset has facilitated refinement of the DOR approach:

Previous approach

- Emissions calculated using static emissions factors taken from the UK SAP 2016 manual[2].
- Weather correction only configured for gas-heated dwellings.
- Required complete 365-day energy demand and ambient temperature dataset.

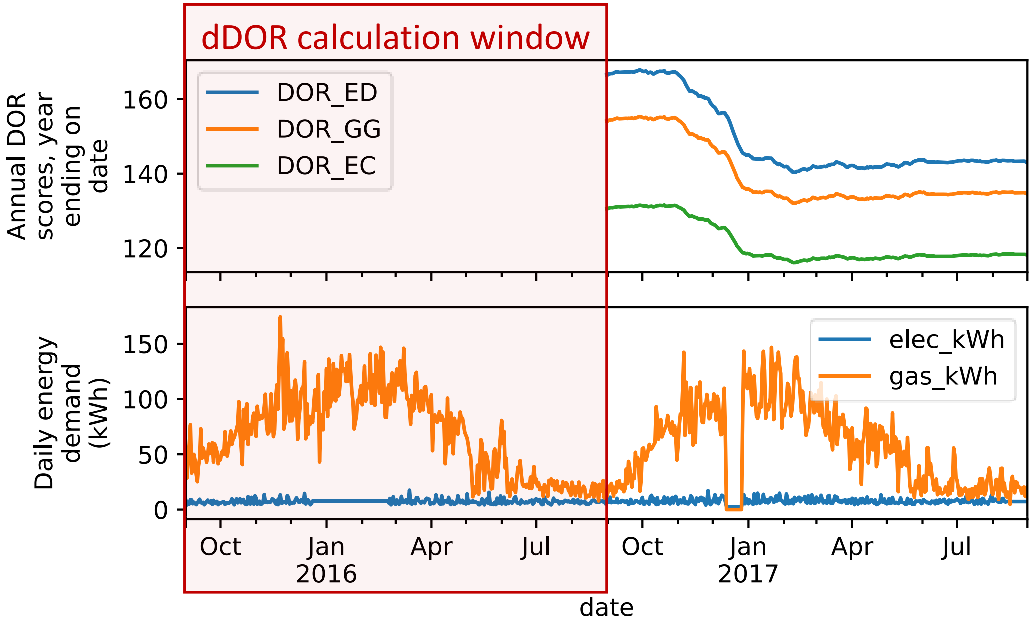
Updated methodology

- Incorporates dynamic electricity emissions calculated using half-hourly carbon intensity data sourced from National Grid ESO[3].
- Weather correction algorithm generalised for application to dwellings with gas or electric heating.
- Correction factor applied to estimate energy demand for up to 30 missing days.

2. BRE, 2016. *The Government's Standard Assessment Procedure for Energy Rating of Dwellings, Draft 2016 edition for consultation.* BRE, London.
3. National Grid Electricity System Operator, 2022. *Historic Generation Mix & Carbon Intensity*. National Grid ESO, UK.

DOR – application to SERL dataset

- Refined DOR algorithm coded in Python, applied to all dwellings in the SERL dataset[4] with data available for at least one full year (some 4400 dwellings).
- Applied to rolling year-long windows:



(Image produced from analysis of non-SERL data)

Energy demand score

$$DOR\_ED = 100 \times \frac{\text{Weather−corrected annual energy demand}}{\text{Benchmark annual energy demand}}$$

GHG emissions score

$$DOR\_GG = 100 \times \frac{\text{Associated annual GHG emissions}}{\text{Benchmark annual GHG emissions}}$$

Energy cost score

$$DOR\_EC = 100 \times \frac{\text{Associated annual energy cost}}{\text{Benchmark annual energy cost}}$$

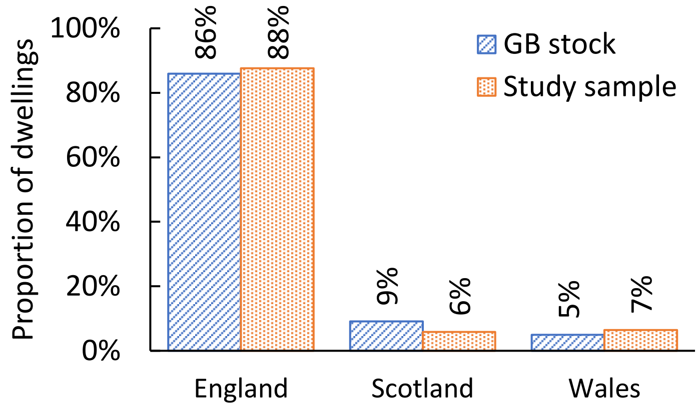
4. Elam et al., 2022. *Smart Energy Research Lab Observatory Data, 2019-2021: Secure Access*. [data collection]. UK Data Service.

Analysis – factors influencing domestic energy demand

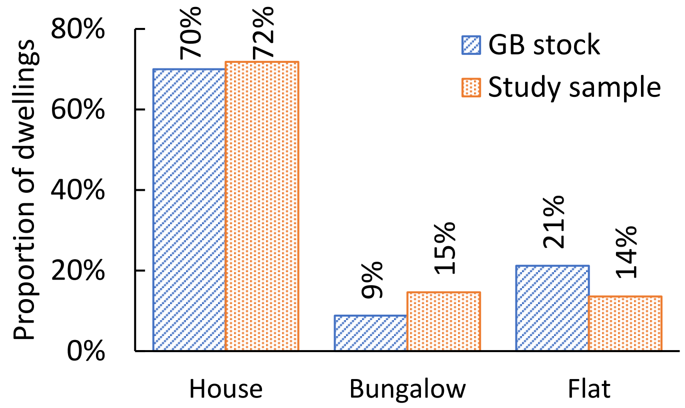
- Sample restricted to those dwellings for which a DOR calculation was possible for a fixed study year, ending December 2021. (N = 3753)
- Restricted again to those with accompanying building & sociotechnical data describing: (N = 2323)
  - Building characteristics (built form, construction, heating system…)
  - Occupant behaviours (use of heating, window opening…)
  - Household characteristics (household size, tenure, age, employment…)
  - Appliance ownership
- LASSO (Least Absolute Shrinkage and Selection Operator) regression approach applied to produce linear models of DOR-measured annual energy demand as a function of the 4 independent variable sets above.
- Models constructed using individual variable sets, and then combined.
- Performance (explanatory power, via R^2 values) of models compared & significant predictors identified

Analysis – representation of GB stock

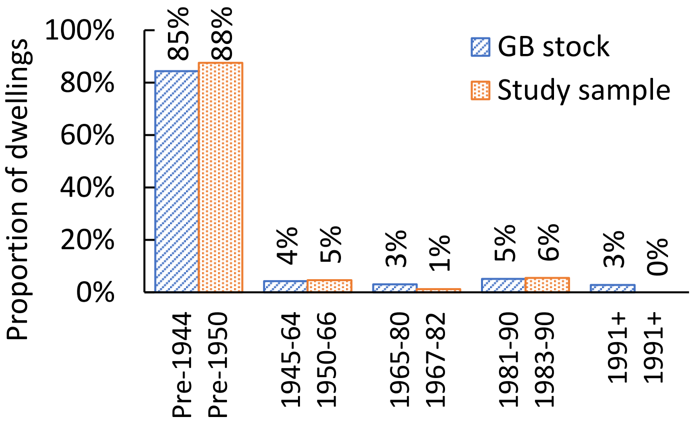
GB stock[5]
Study sample



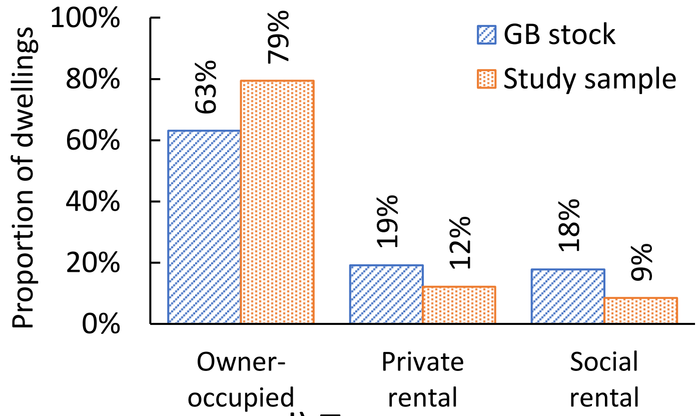
a) Geographic region.



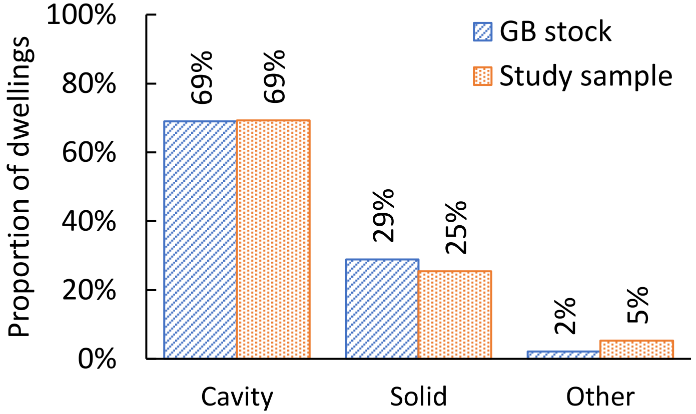
b) Property type.



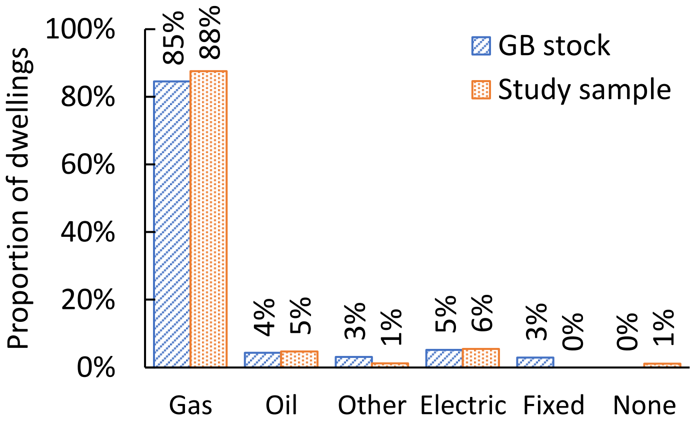
c) Construction age band.



d) Tenure.



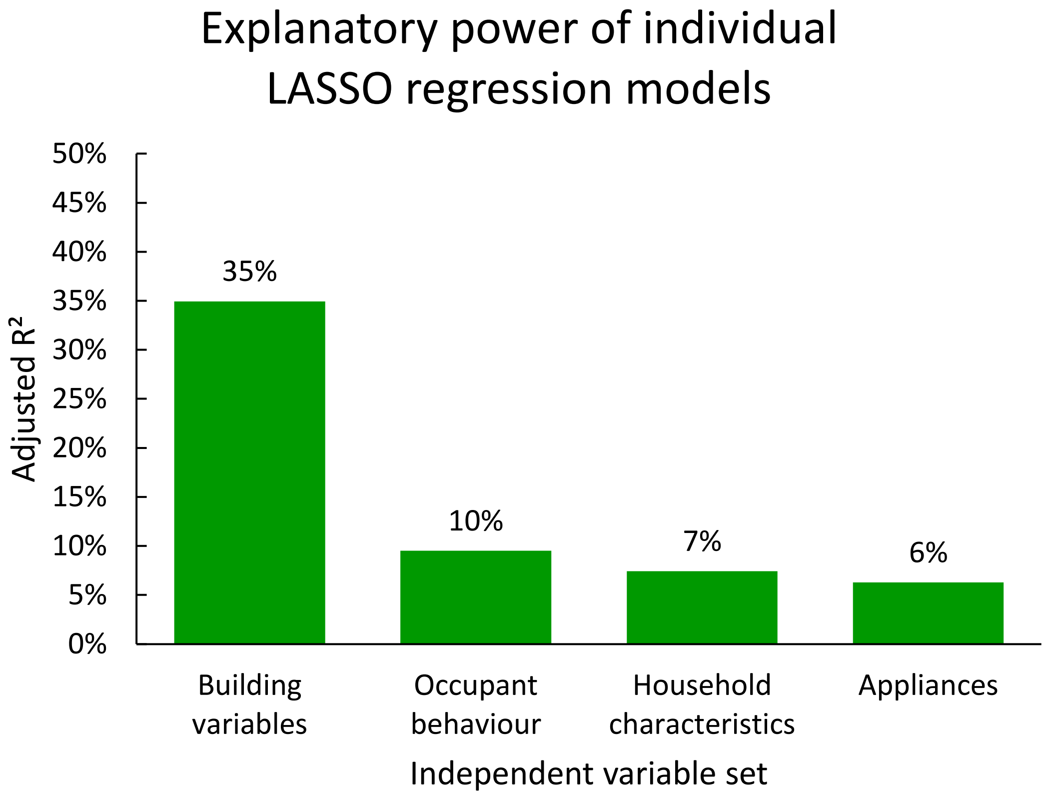
e) Main wall construction.



f) Central heating type (GB) or main heating fuel fix (S2323).

5. BRE, 2020. *The Housing Stock of the United Kingdom*. BRE Trust.

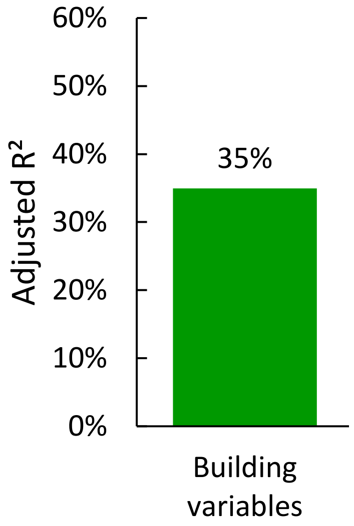
Findings: Factors influencing UK domestic energy demand



- Building variables model had greatest explanatory power.
- Significant predictors also identified among other variable sets, but could be correlated with building variables.
- Next step: produce combined models using combined independent variable sets, applying LASSO to eliminate collinearity.

Findings: Factors influencing UK domestic energy demand

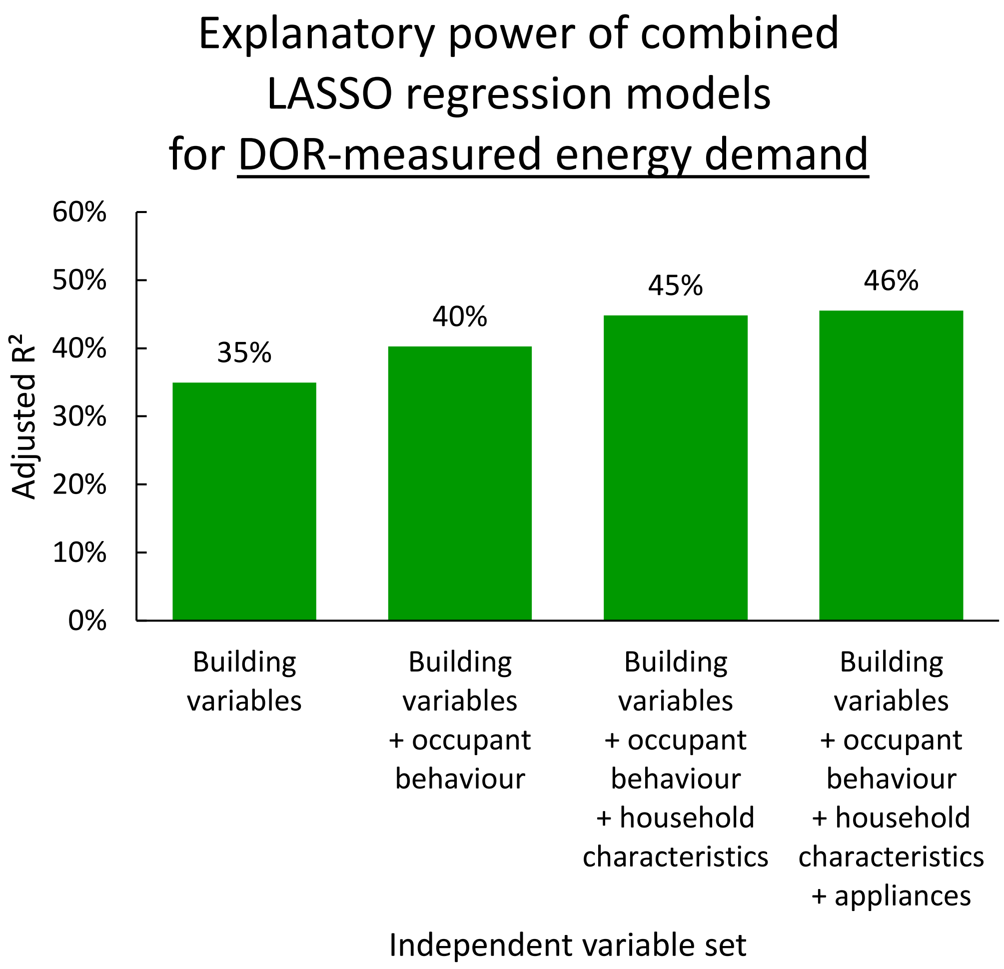
Explanatory power of combined LASSO regression models

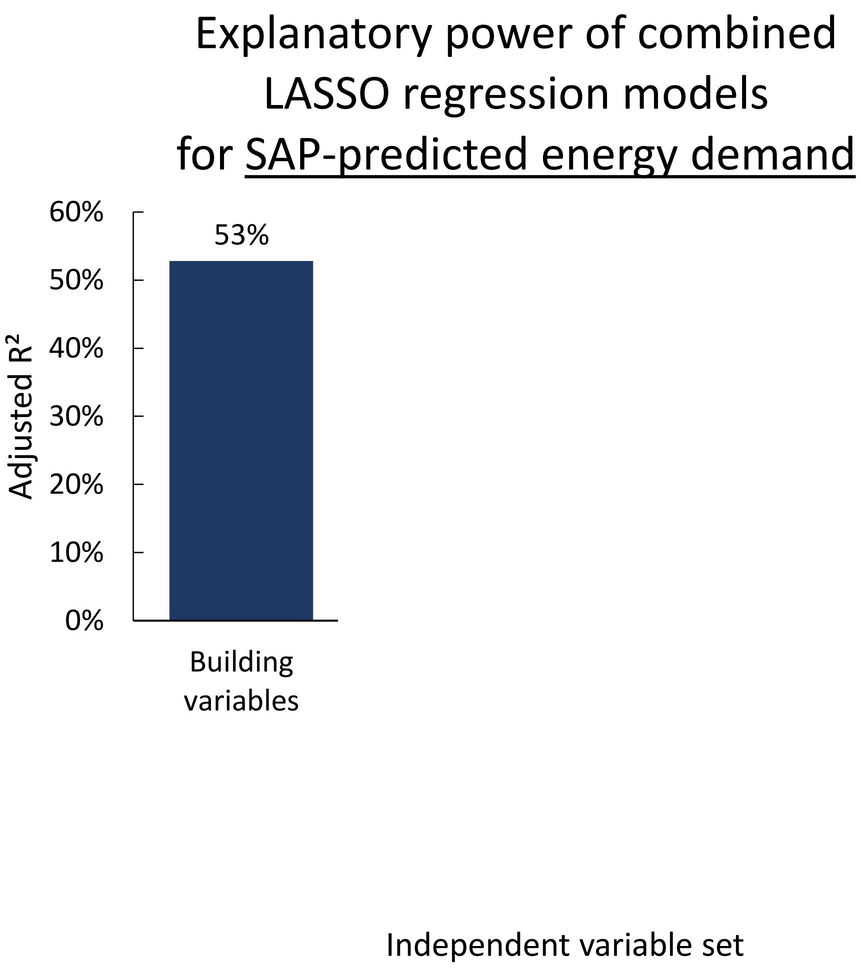


Independent variable set

- Significant ($p < 0.001$) increases in explanatory power when introducing each successive set of variables.
- Q: How does this compare with UK SAP?
- Analysis was repeated using the SAP-predicted energy demand as the dependent variable rather than DOR-measured energy demand

Findings: Factors influencing UK domestic energy demand





Findings: Factors influencing UK domestic energy demand

Significant ($p < 0.05$) predictors of DOR energy demand score & SAP in final combined model spread across all 4 variable sets:

Variable set	Number of significant predictors in final combined model	
	for DOR-measured energy demand	for SAP-predicted energy demand
Building variables	19	24
Occupant behaviour	7	2
Household characteristics	4	0
Appliances	4	1

15 non-building variables

3 non-building variables

Significant predictors of measured demand generally consistent with previous findings.

Findings: Factors influencing UK domestic energy demand

Key findings

- **Domestic energy demand is sensitive to sociotechnical factors not accounted for in SAP**
  Building variables explained only 35% of variability in DOR-measured demand, compared with 53% of SAP-predicted demand. Including household and behaviour variables significantly improved explanatory power for DOR, but not for SAP energy demand.

- **Influence of some building variables may be overestimated in SAP**
  Some variables identified as significant predictors of SAP-predicted energy demand, but not of DOR-measured demand (e.g., proportion of low energy lighting; number of open fireplaces; wall insulation status).

- **Influence of some building variables may be underestimated in SAP**
  Some were significant predictors of DOR-measured demand, but not SAP-predicted (e.g., being a bungalow [vs house]; absence of main heating system [vs gas central heating]).

Outputs & future work

- Working paper

  Factors influencing measured and predicted UK dwelling energy demand.
  Released from SecureLab & currently being worked up into journal paper.

- Planned paper:

  Domestic operational rating for UK homes: application to electrically heated dwellings.
  To report refinement of the DOR methodology for application to electrically heated homes.

- What next? (With EDOL?)

  Further development of DOR to incorporate dynamic pricing & self-consumption.

  Analysis of how DOR scores evolve over time, in particular their response to energy-driven retrofit & interventions.

  Analysis of relationships between DOR and other metrics describing in-use building performance.

Domestic operational rating (DOR): development, programming and testing

Matt Li & Kevin Lomas
Building Energy Research Group, Loughborough University

2023-Dec-06

Loughborough University

References

BRE, 2016. *The Government's Standard Assessment Procedure for Energy Rating of Dwellings, Draft 2016 edition for consultation.* BRE, London.

BRE, 2020. *The Housing Stock of the United Kingdom*. BRE, London.

Elam et al., 2022. *Smart Energy Research Lab Observatory Data, 2019-2021: Secure Access*. [data collection]. UK Data Service.

Lomas et al., 2019. *A domestic operational rating for UK homes: Concept, formulation and application*. Energy & Buildings 201, 90-117.

National Grid Electricity System Operator, 2022. *Historic Generation Mix & Carbon Intensity*. National Grid ESO, UK.

Quantifying the heat-up time period from smart meter data

Dr Adam Hardy & Professor David Johnston
Leeds Beckett University

Introduction

Aim:

- To determine whether it is possible to derive a new in-use performance metric related to the Heat-Up Time (HUT) of domestic space heating systems from smart meter data.

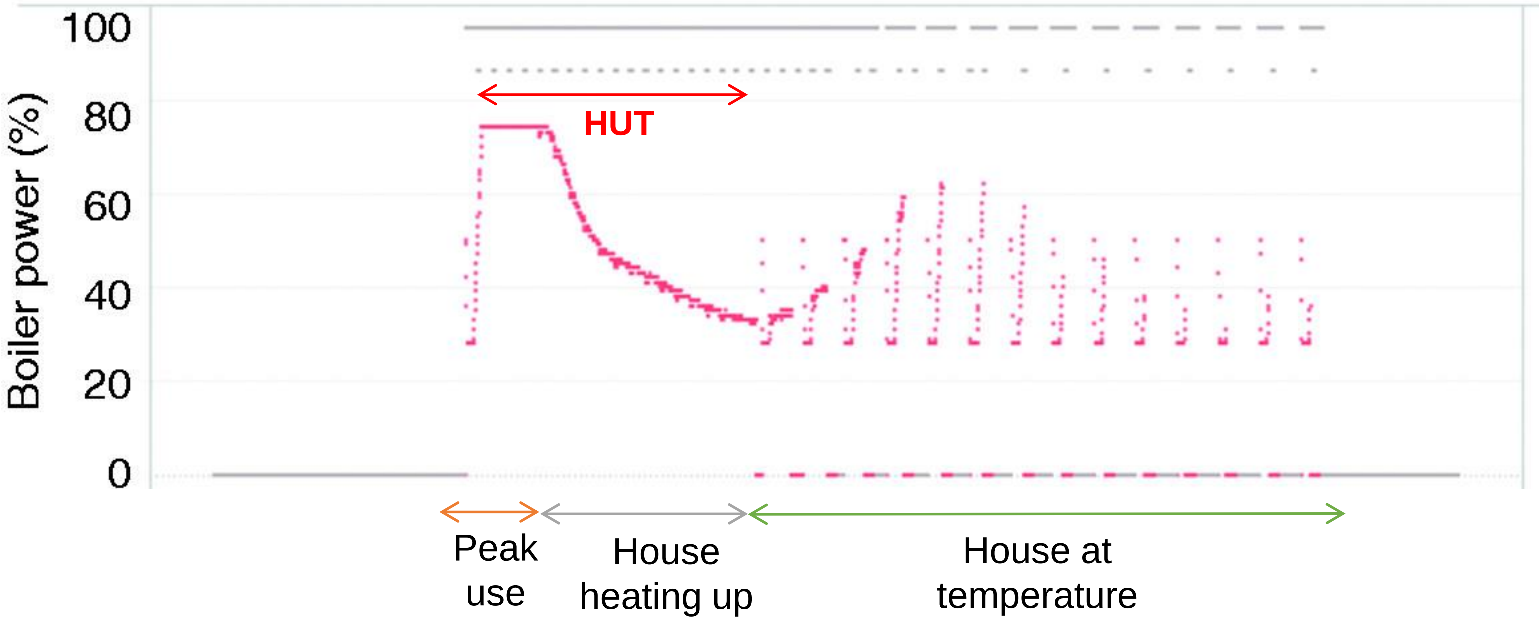
HUT defined as the time between the boiler activating and then deactivating and cycling as the setpoint temperature is reached.

Metric could be used to:

- Characterise the thermal response of a dwelling and identify those dwellings where appropriate interventions should be installed to improve their thermal response.
- Identify those dwellings where the central heating set point temperature is unlikely to have been achieved.
- Identify those dwellings that are likely to be most vulnerable to extreme cold weather events.

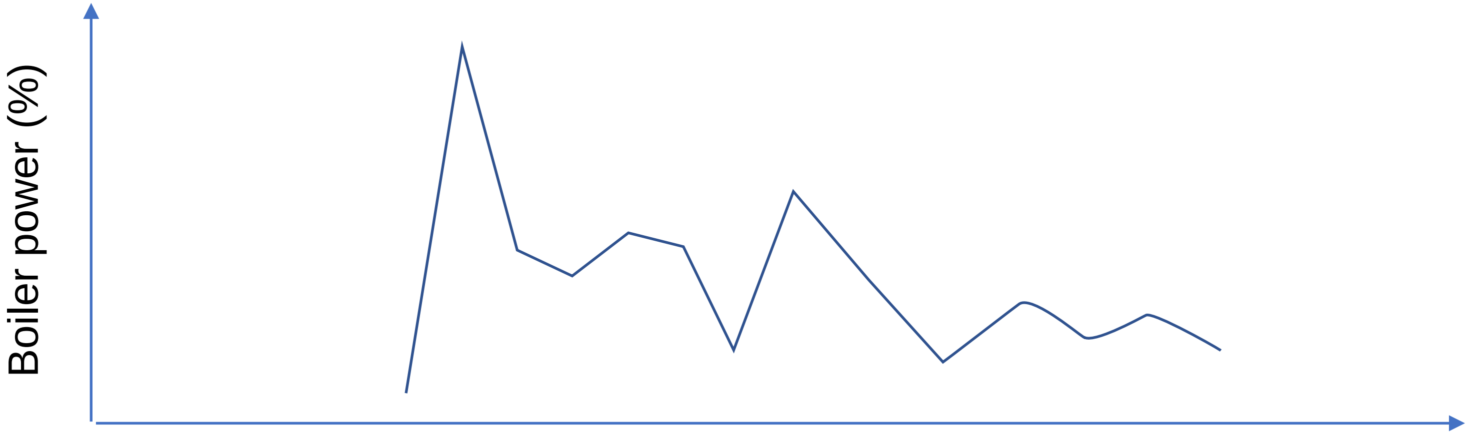
First Challenge – How well can we determine HUT from smart meter data?

Example Boiler profiles – 1-minute vs 30-minute resolution.



High resolution – 1-minute

Source: Bennett (2020)



Low resolution – 30-minute

Bennett, G. (2020) Heating systems through the lens of the boiler: Detailed case studies to inform current and future heating system design. *Building Services Engineering Research and Technology*. 41 (3):332-342.

Reference models

No database of real boiler use at 1-minute intervals existed, so one was created.

- Reference models created at 1-minute resolution.
- Models varied in their heat-up times, modulation, and cycling frequencies.
- Total of 742,500 reference models created.
- Models down sampled at 30-minute intervals to replicate smart meter data.

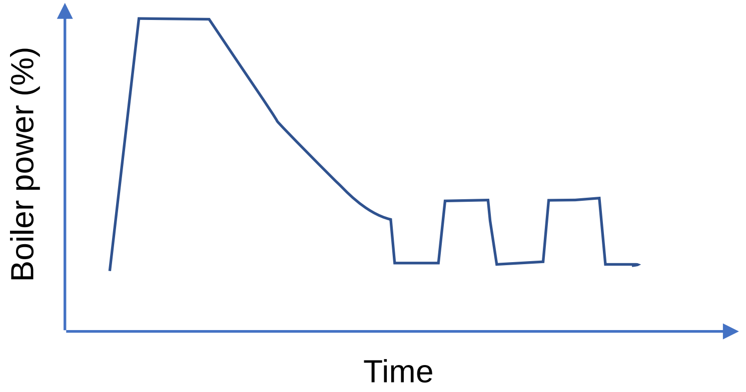
Variable	Description	Values
Start time	Start time within a 30-minute window	0, 5, 10, 15, 20, 25
Peak runtime	Time spent as maximum boiler load, in minutes	5, 15, 25, 35, 45
Thermostat cutoff time	Time from the peak load till the thermostat stops demanding heat, in minutes	20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120
Decay coefficient	How quickly the boiler will decay from maximum to minimum modulation.	0.02, 0.04, 0.06, 0.08, 0.1
Minimum modulation	Minimum modulation the boiler is capable of.	1:10, 1:8, 1:6, 1:5 and 1:4
Cycling load	Gas demand during cycling period, as fraction of peak load	0.3, 0.4, 0.5, 0.6, 0.7, 0.8
Cycling deadtime	Time spent in between cycles in minutes	10, 20, 30
Cycling percentage	Percentage of remaining time which is cycled	10%, 25%, 50%, 75%, 100%

More 'realistic' test models

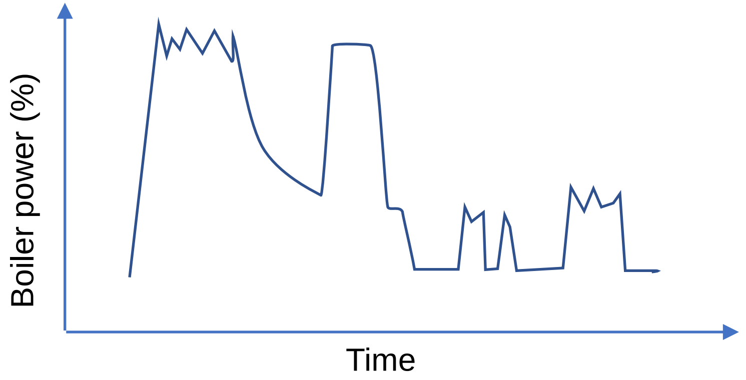
A sub-sample of 1000 test models were randomly selected and used to create a sample of more realistic models.

More realistic test models created by adding:

- Noise.
- Dropouts.
- Periods of hot water use.



Randomly selected model



More realistic model

Comparison of test and reference models

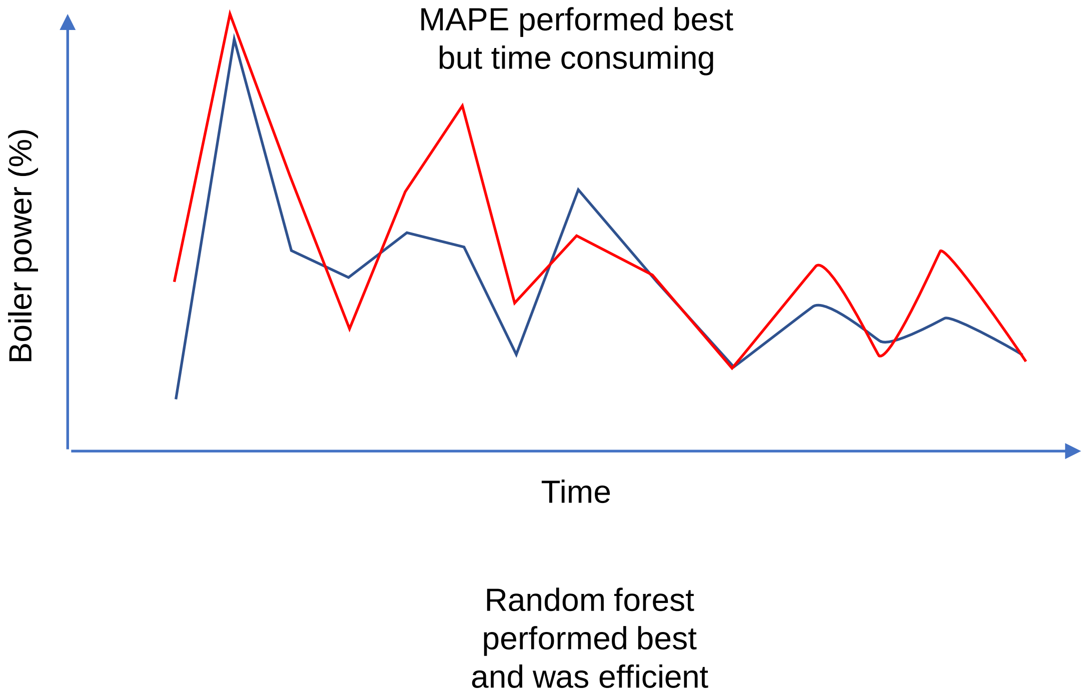
Test models were compared to the reference models using several techniques.

Statistical methods:

- **Euclidean distance** – calculate difference between each set of points and sum.
- **MAPE** – Calculate percentage difference of each set of points and take average.
- **Pearson correlation coefficient** – Measures linear correlation between both data sets.

Machine learning methods:

- **Random Forest.**
- **Gradient Boosted tree.**
- **Neural network.**



Random Forest selected based upon compromise between accuracy and efficiency.

Filtering process

Homes which heat with gas

↓

Heating controlled by thermostat

↓

No secondary heating

↓

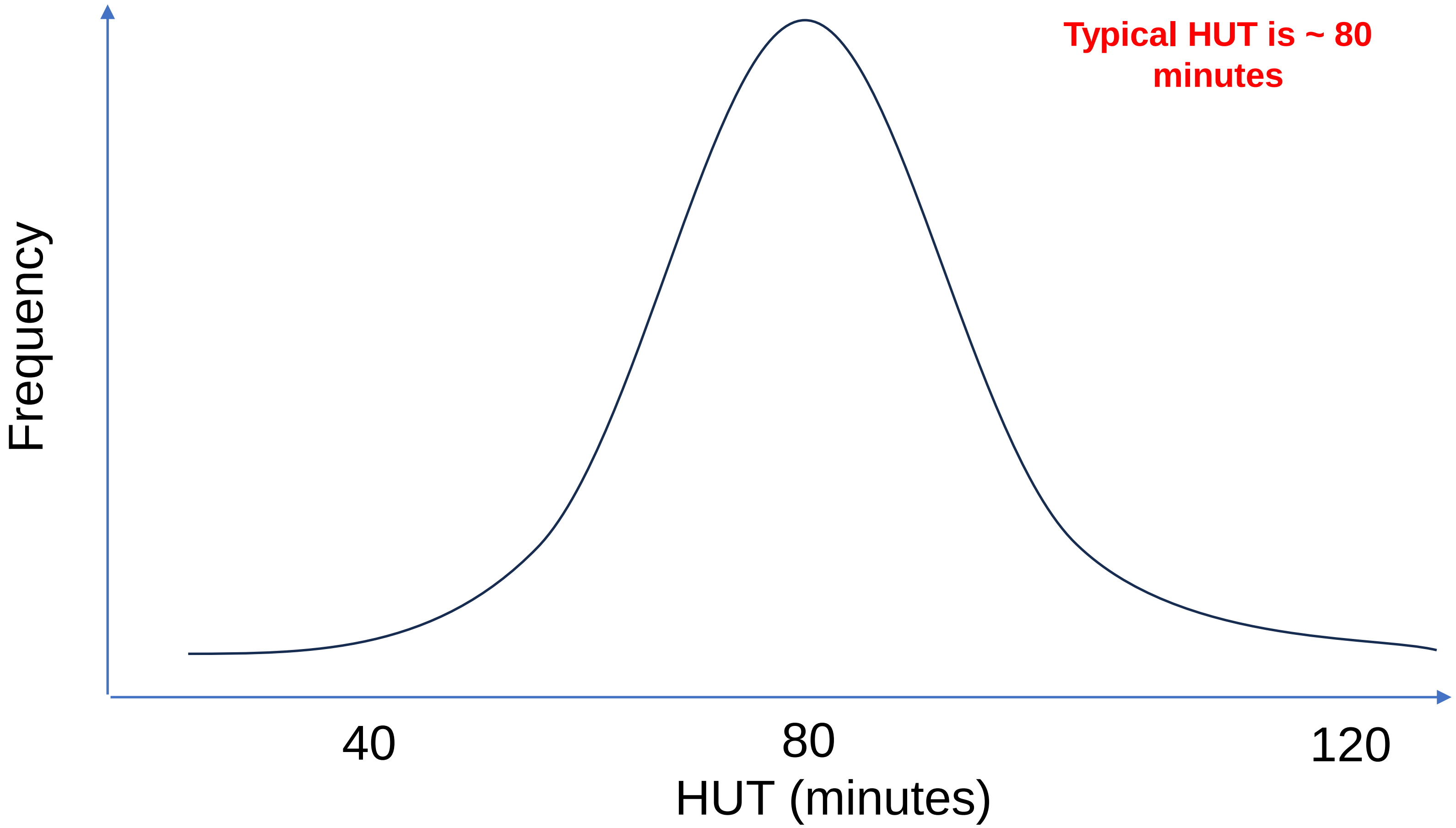
Residents report that they can keep comfortably warm.

↓

Resulted in a sample of ~1900 dwellings

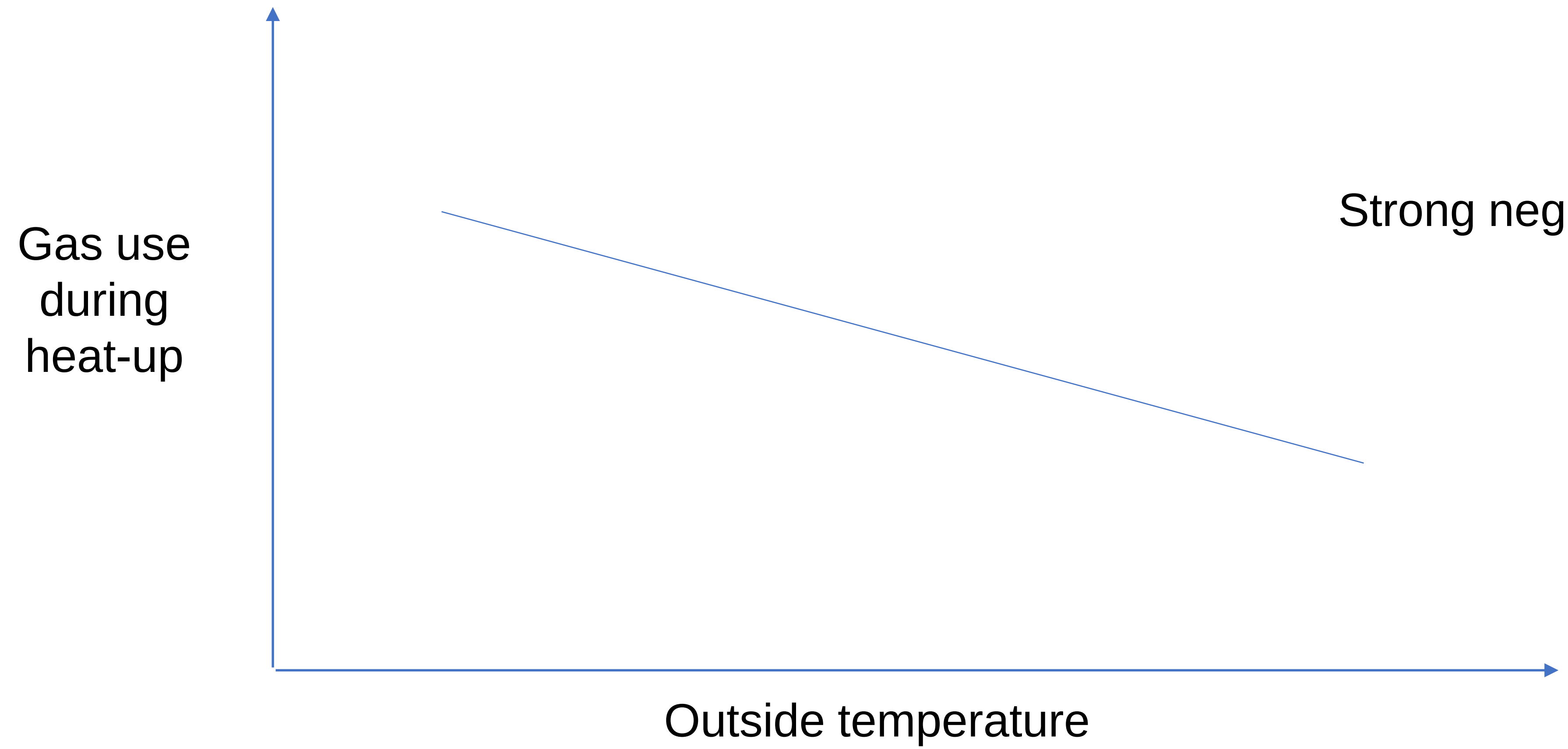
Gas data for the months of December, January and February were then isolated for further analysis.

HUT distribution



Results

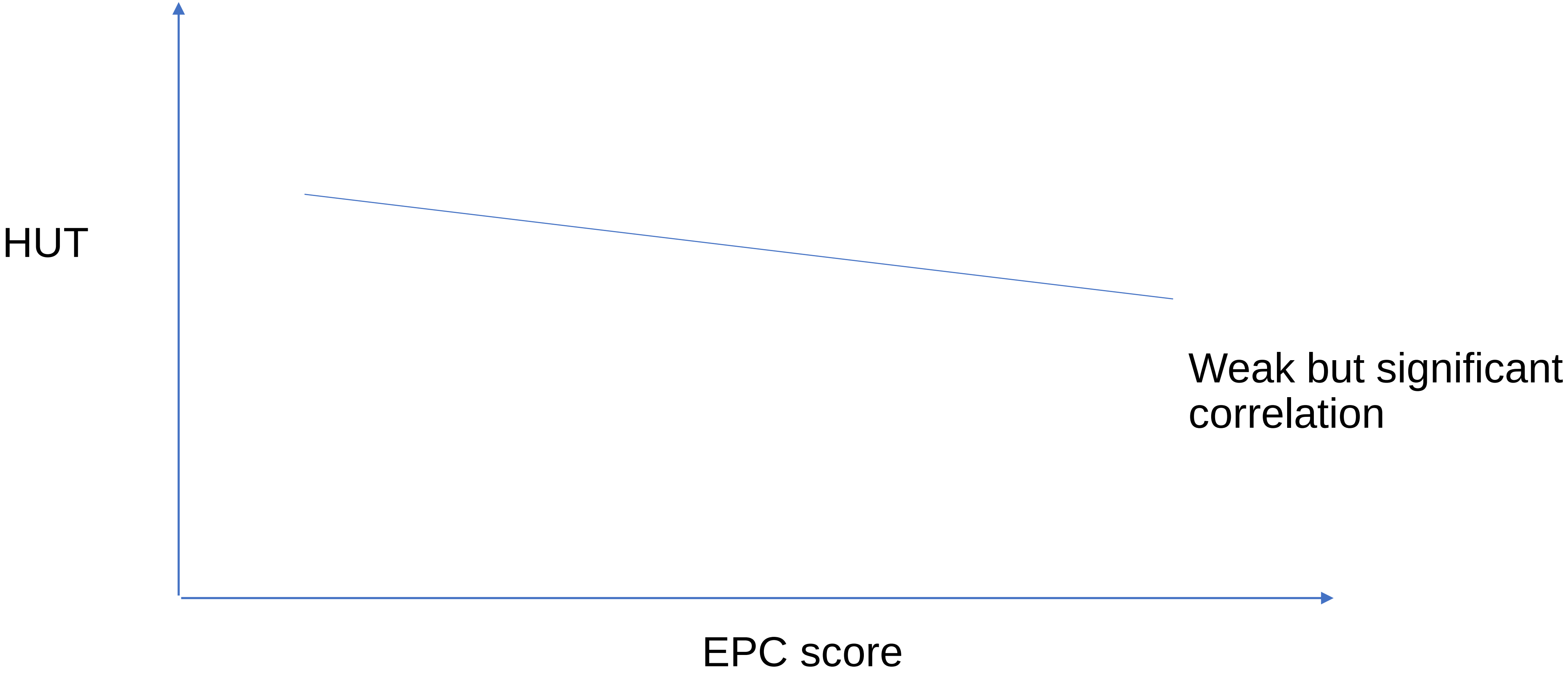
Gas use vs outdoor temperature



No significant correlation with other weather variables.

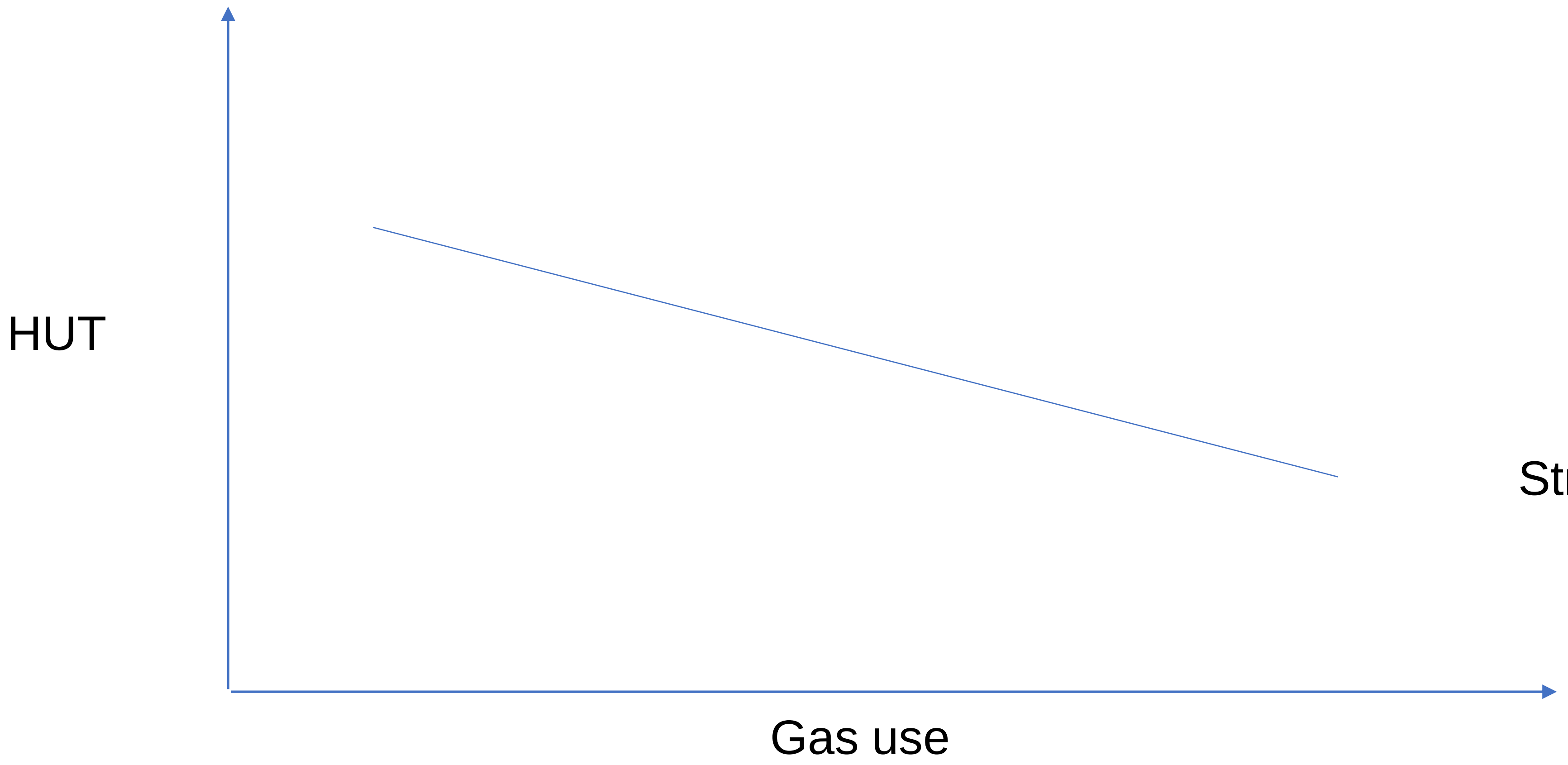
Results

HUT vs EPC score



Surprising results

HUT vs gas use



Strong correlation

Homes with low gas use heat up slower – may be reflective of oversizing of boilers, cycling behaviour and/or inefficient heating systems.

Conclusions

- **It is possible to gain an understanding of HUT from smart meter gas data.**
- **Trends in HUT generally as expected, although there are some surprises.**
- **May be possible to more accurately predict HUT from EPC data in the future.**

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Do EPCs reflect real world performance? A comparison between smart meter and EPC data

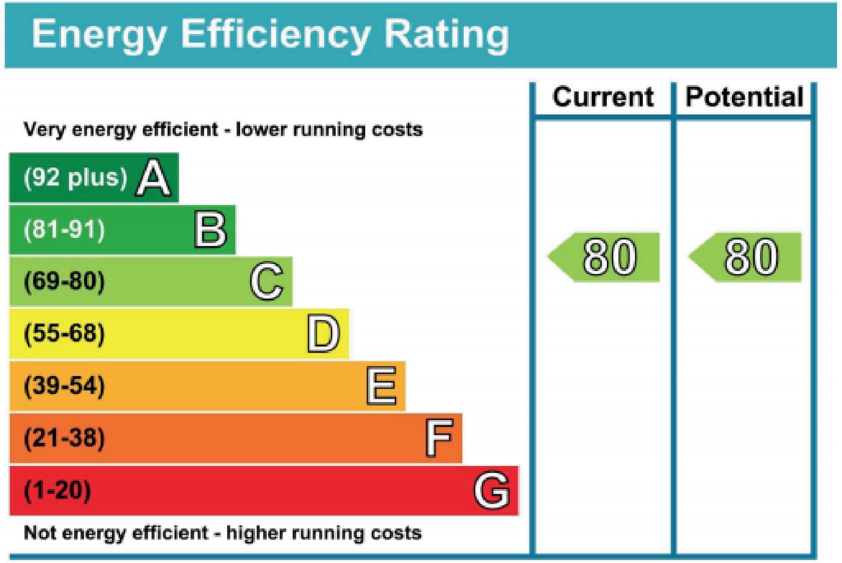
Dr Jessica Few

Senior Research Fellow

UCL Energy Institute

Context

- EPCs were introduced to increase the transparency of building energy efficiency
- Millions of homes have one: 1.5 million lodged in 2021
- Increasingly relied on for policy interventions
  - E.g. all rented homes must be at least EPC E at present, rising to C from 2025
- However, there is concern over the scale of the difference between EPC modelled energy use and actual energy use



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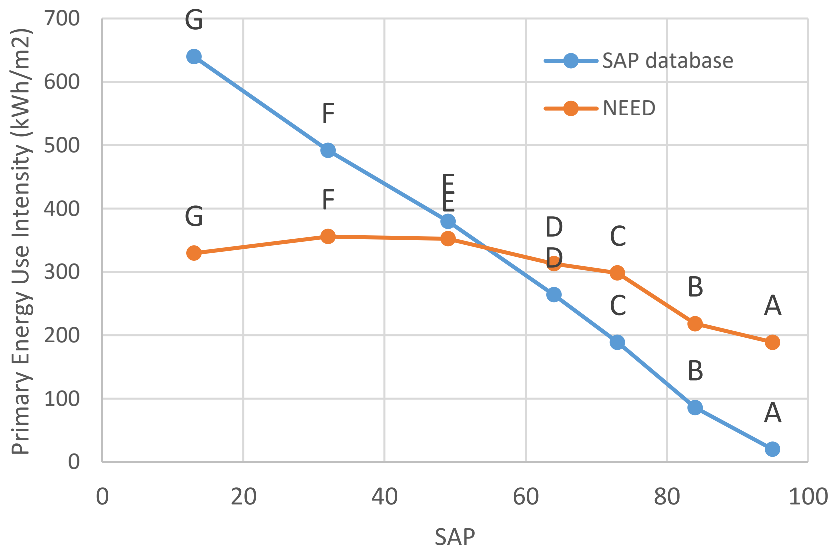
Previous analysis: no data is perfect

- Many previous papers and reports suggested a discrepancy between metered data and SAP predictions, e.g. with NEED and EFUS. This in part drives the EPC action plan.

- This is unsurprising because:

  - SAP assumes a normative use of energy services
  - EPCs do not report energy use for appliances or cooking
  - EPC rating is derived from fuel cost (including standing charges) not metered energy (so you are comparing apples and oranges)
  - Most comparisons do not account for un-metered energy.

Primary energy use intensity (kWh/m^2) versus SAP using data from the EPC database and NEED gas and electric data from 2020 NEED report



Our analysis attempts to overcome the above challenges

Electricity data

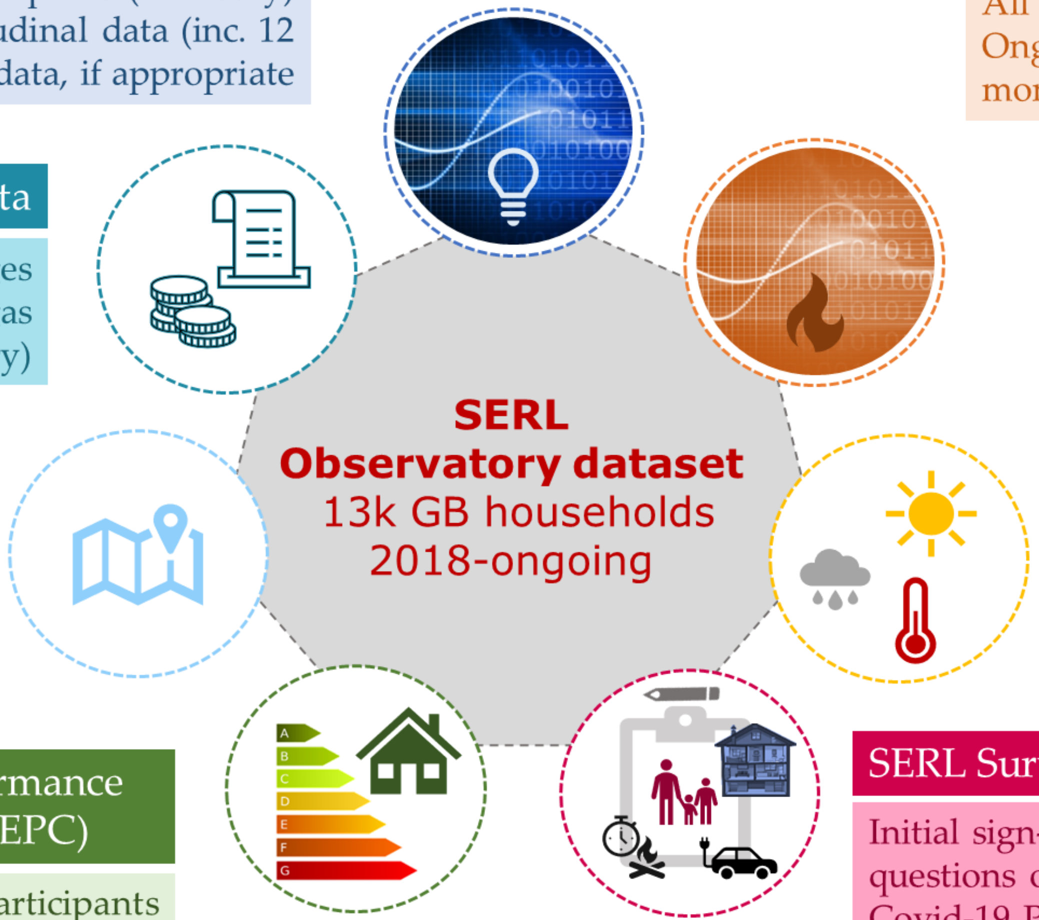
Energy data: Daily, half-hourly
All participants (in theory)
Ongoing longitudinal data (inc. 12 months historic data, if appropriate

Gas data

Energy data: Daily, half-hourly
All participants with gas meter
Ongoing longitudinal data (inc. 12 months historic data, if appropriate)

Tariff data

Unit and standing charges for electricity and gas
All participants (in theory)



Weather data

ECMWF ERA5 data
Hourly longitudinal data
30km resolution
24 variables

Location data

Region, LSOA, IMD quintile
All participants

Energy Performance Certificate (EPC)

~50% of participants
Sourced from EPC Register

SERL Surveys

Initial sign-up survey (2019-2021): 40 questions on the dwelling and household
Covid-19 Pandemic survey (2020)
Cost of living / energy costs survey (2023)

UKDS study number 8666
Data descriptor paper: Webborn *et al.* (2021)
Statistical report: Few *et al.* (2022)

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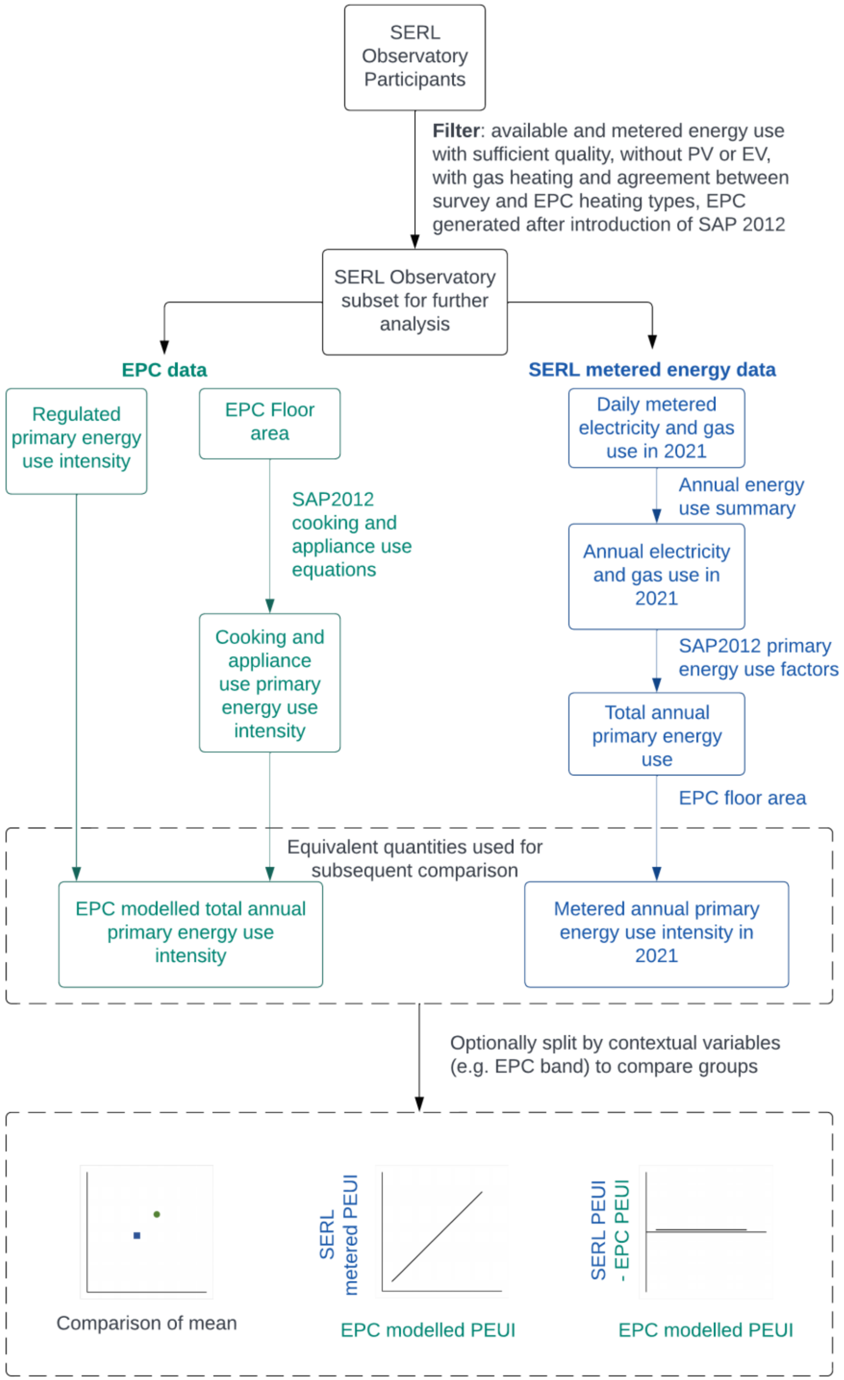
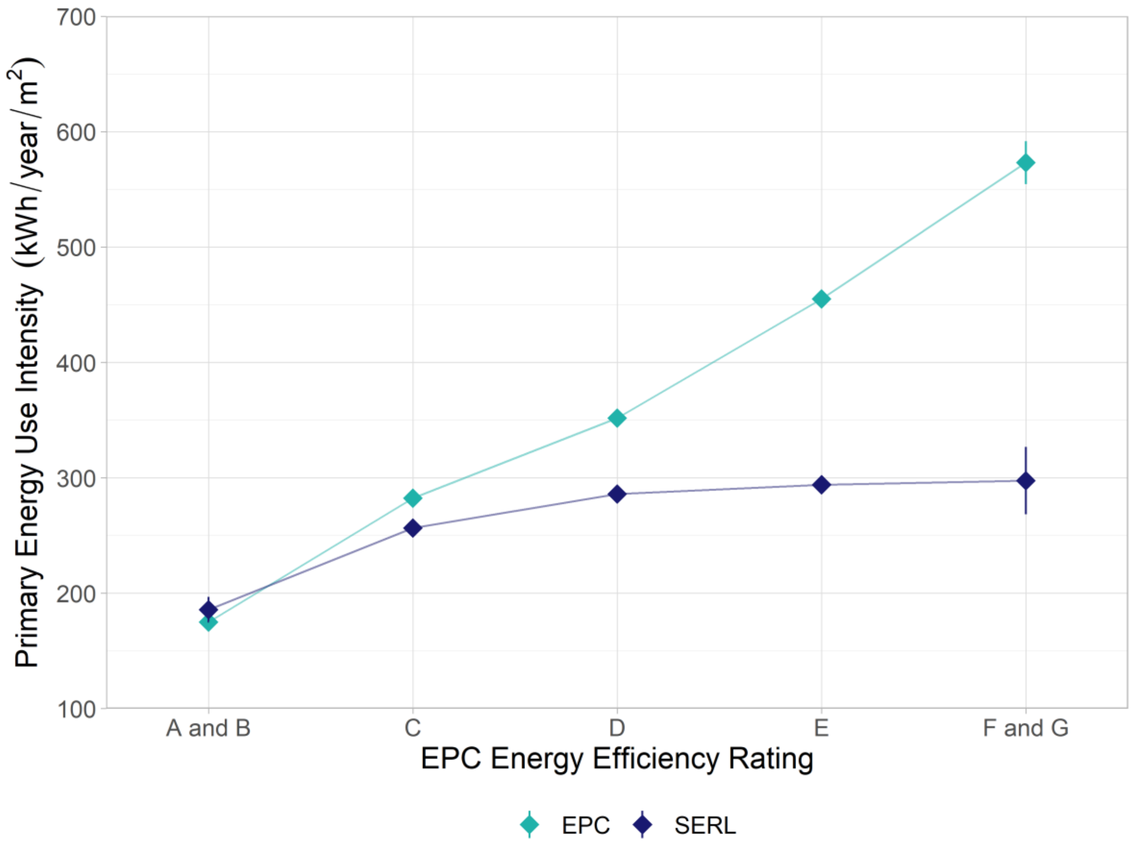
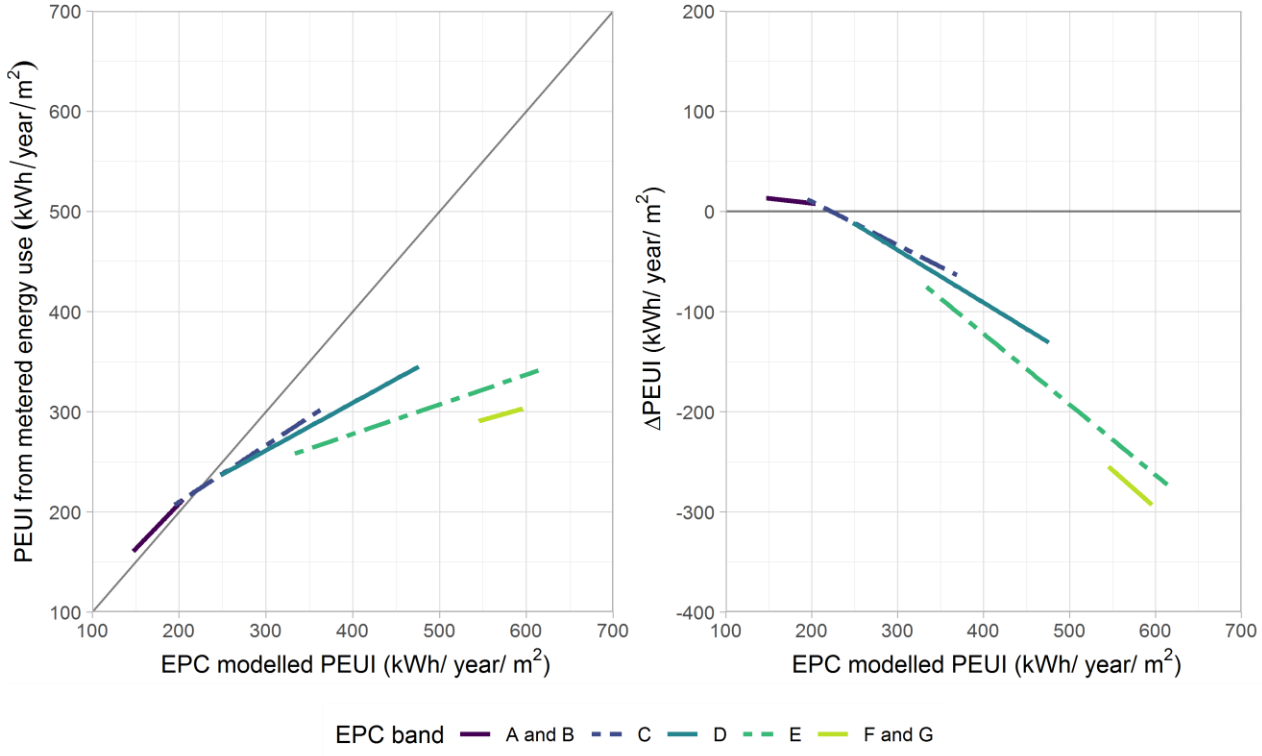

SERL Observatory Participants
Filter: available and metered energy use with sufficient quality, without PV or EV, with gas heating and agreement between survey and EPC heating types, EPC generated after introduction of SAP 2012
SERL Observatory subset for further analysis
EPC data
SERL metered energy data
Regulated primary energy use intensity
EPC Floor area
SAP2012 cooking and appliance use equations
Cooking and appliance use primary energy use intensity
Daily metered electricity and gas use in 2021
Annual energy use summary
Annual electricity and gas use in 2021
SAP2012 primary energy use factors
Total annual primary energy use
EPC floor area
Equivalent quantities used for subsequent comparison
EPC modelled total annual primary energy use intensity
Metered annual primary energy use intensity in 2021
Optionally split by contextual variables (e.g. EPC band) to compare groups
Comparison of mean
SERL metered PEUI
EPC modelled PEUI
SERL PEUI - EPC PEUI
EPC modelled PEUI

EPCs overpredict energy use in C to G properties, and over predict the change between bands





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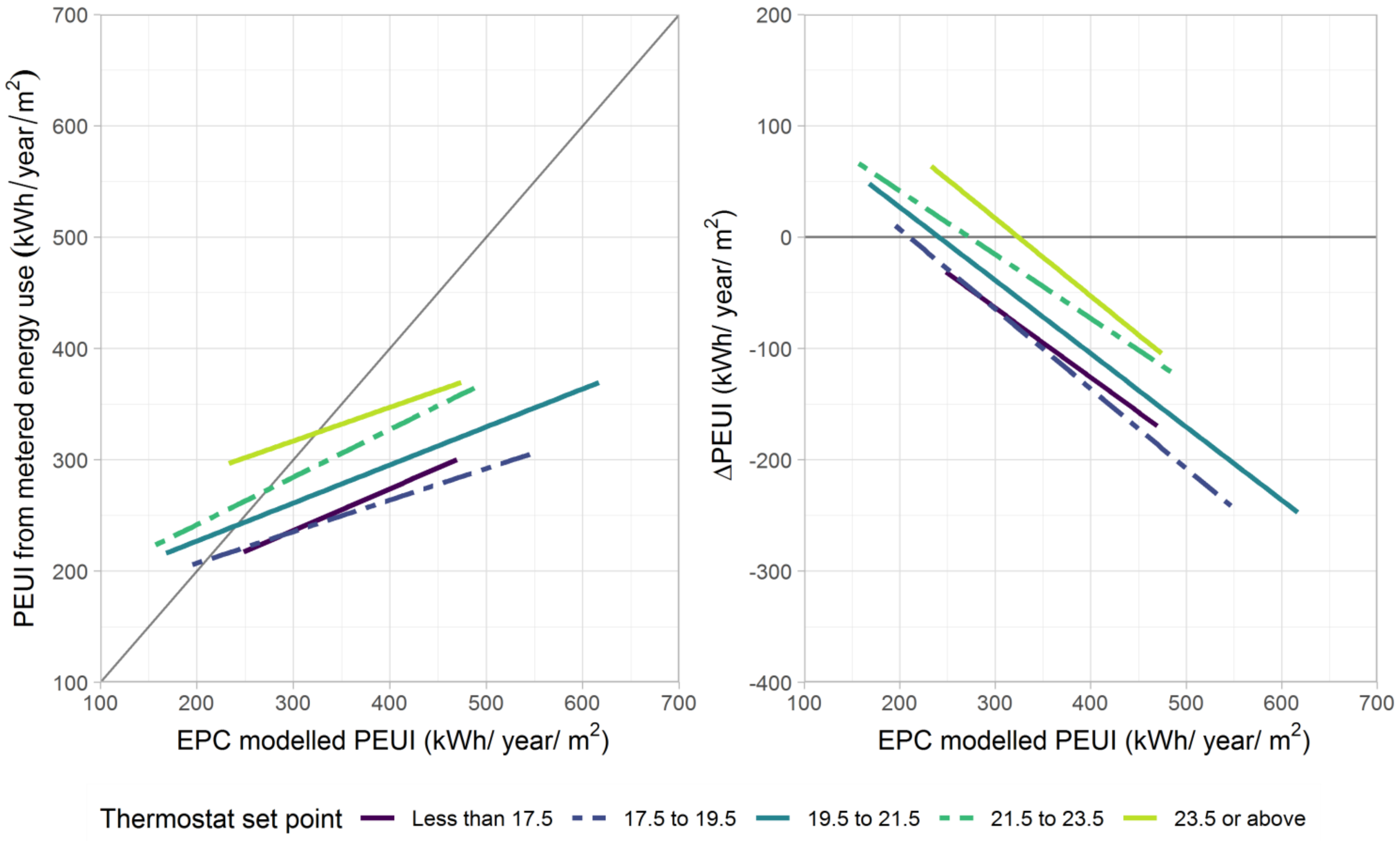
Thermostat set point

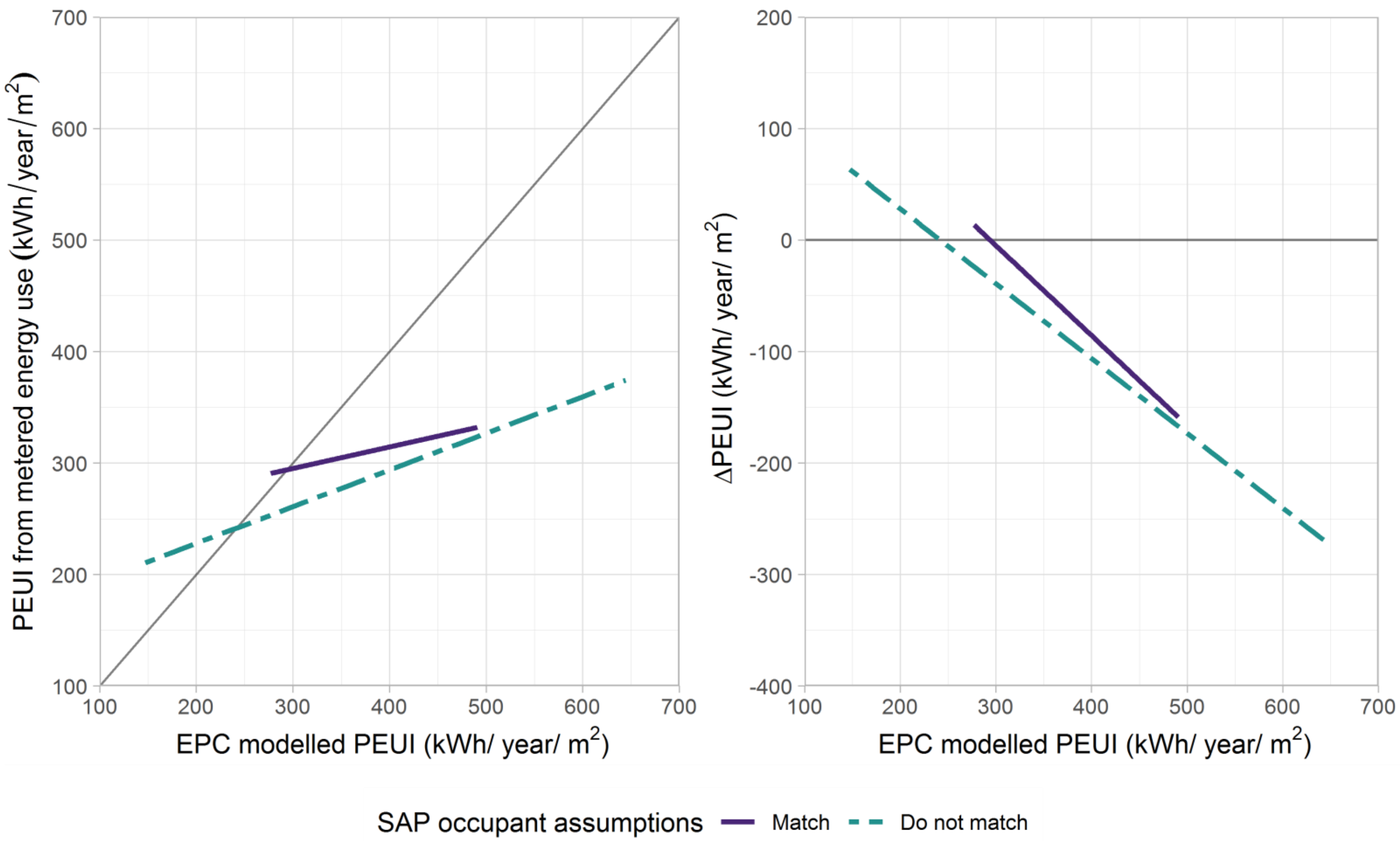


- As expected, an increased thermostat set point is associated with higher metered energy use
- But this has little impact on the gradient of metered to EPC modelled energy use.

The SAP model assumptions do not appear to explain the discrepancy

We classify homes as matching the SAP occupant assumptions if:

- The number of occupants assumed by the model agrees with the SERL survey to the nearest integer
- The reported thermostat set point is 20.5 to 21.5
- Occupants report heating their whole home
- Occupants report that the home is comfortably warm
- Occupants are not struggling financially



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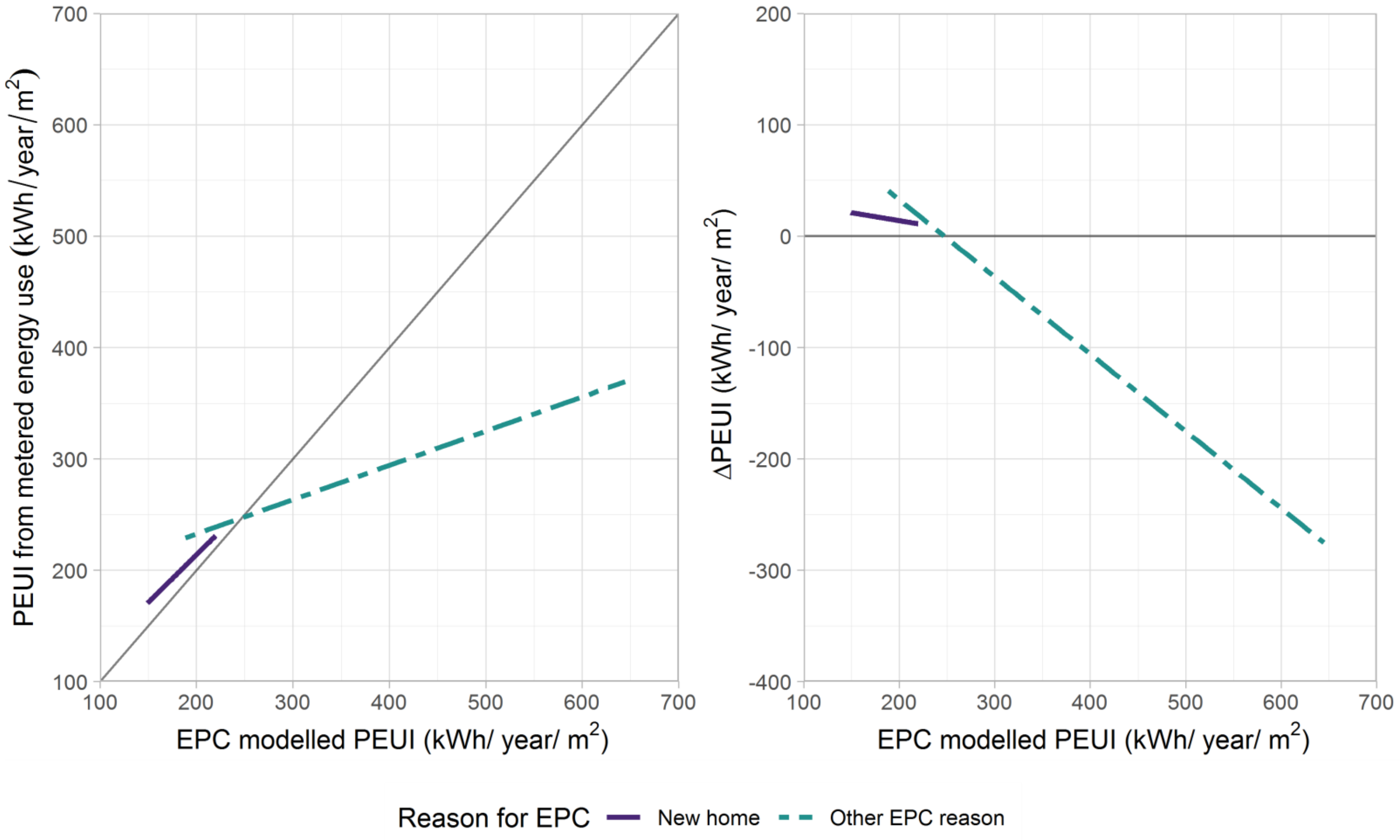
New homes rated via full SAP show good agreement



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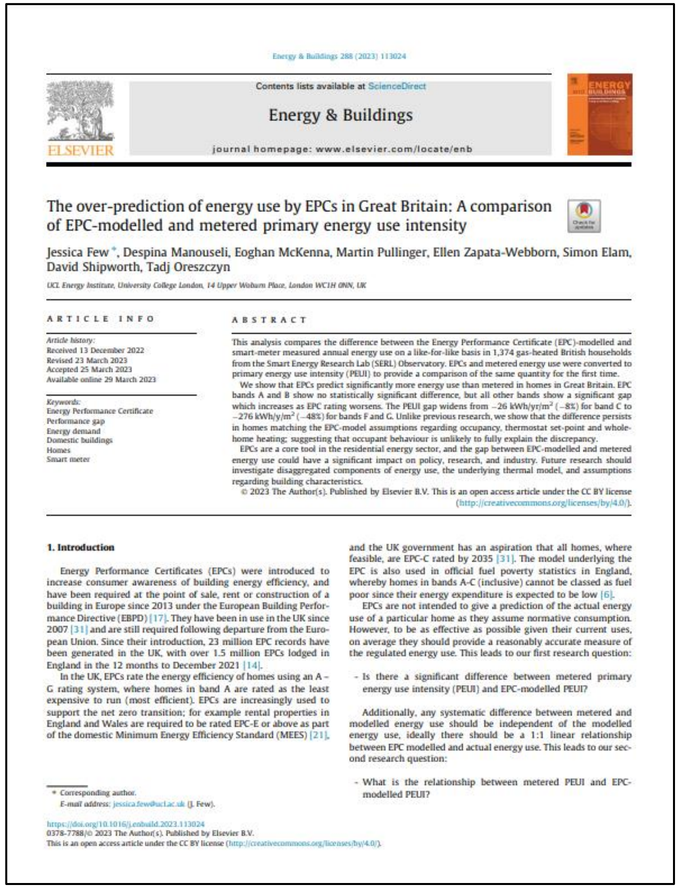
Hypothesised causes of gap

1. **Core Calculation:**
   a. **Mean Internal Temperatures** (MIT) is not modelled correctly with changing energy efficiency?
   b. **Heating system and controls** (over simplified, no radiator sizing, etc)
2. **Inputs - Assumptions**
   a. **Heat loss**: Theoretical calculations overestimate the heat loss from uninsulated properties and underestimate the heat loss of well insulated properties, (HTC) (solid walls, floor insulation and ventilation may be a key factor in heat loss).
   b. **Heating profiles** (24hr and weekend-weekday)
   c. **Hot water and lights & appliance use** (the use of primary energy use intensity as the public energy metric distorts the importance of appliances, fans and pumps)
3. **EPC Process**
   a. **Out-dated EPCs:** The EPC Registry contains historic EPCs calculated using different vintages of SAP/RdSAP, assuming different conventions, assumptions and versions. Two effects:
      a. Errors in the historic EPC process (e.g. changes to assumptions and conventions). (HTC & Efficiency)
      b. Interventions post EPC rating such as replacement boilers and windows (HTC & Efficiency)
   b. **RdSAP vs SAP: Motivation & Defaults**. EPC assessors are incentivised by the process and those commissioning EPCs to rate existing homes poorly via RdSAP (‘The Default Effect’ and ‘Fear of Audit Effect’) and new insulated homes via SAP as good. (HTC & Efficiency)

Summary

- We did an apples-for-apples comparison of metered vs EPC modelled PEUI
- There is a big spread, but regardless of how we split the data we see that the SAP calculation increasingly overestimates PEUI as modelled PEUI increases
- Occupancy factors make a difference, but this does not appear to explain the shape of the discrepancy.



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journal homepage: www.elsevier.com/locate/enb

ELSEVIER

The over-prediction of energy use by EPCs in Great Britain: A comparison of EPC-modelled and metered primary energy use intensity

Jessica Few *, Despina Manouseli, Eoghan McKenna, Martin Pullinger, Ellen Zapata-Webborn, Simon Elam, David Shipworth, Tadj Oreszczyn

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A R T I C L E I N F O

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Keywords:
Energy Performance Certificate
Performance gap
Energy demand
Domestic buildings
Homes
Smart meter

A B S T R A C T

This analysis compares the difference between the Energy Performance Certificate (EPC)-modelled and smart-meter measured annual energy use on a like-for-like basis in 1,374 gas-heated British households from the Smart Energy Research Lab (SERL) Observatory. EPCs and metered energy use were converted to primary energy use intensity (PEUI) to provide a comparison of the same quantity for the first time.

We show that EPCs predict significantly more energy use than metered in homes in Great Britain. EPC bands A and B show no statistically significant difference, but all other bands show a significant gap which increases as EPC rating worsens. The PEUI gap widens from −26 kWh/yr/m^2 (−8%) for band C to −276 kWh/y/m^2 (−48%) for bands F and G. Unlike previous research, we show that the difference persists in homes matching the EPC-model assumptions regarding occupancy, thermostat set-point and whole-home heating; suggesting that occupant behaviour is unlikely to fully explain the discrepancy.

EPCs are a core tool in the residential energy sector, and the gap between EPC-modelled and metered energy use could have a significant impact on policy, research, and industry. Future research should investigate disaggregated components of energy use, the underlying thermal model, and assumptions regarding building characteristics.

1. Introduction

Energy Performance Certificates (EPCs) were introduced to increase consumer awareness of building energy efficiency, and have been required at the point of sale, rent or construction of a building in Europe since 2013 under the European Building Performance Directive (EBPD) [17]. They have been in use in the UK since 2007 [31] and are still required following departure from the European Union. Since their introduction, 23 million EPC records have been generated in the UK, with over 1.5 million EPCs lodged in England in the 12 months to December 2021 [14].

In the UK, EPCs rate the energy efficiency of homes using an A – G rating system, where homes in band A are rated as the least expensive to run (most efficient). EPCs are increasingly used to support the net zero transition; for example rental properties in England and Wales are required to be rated EPC-E or above as part of the domestic Minimum Energy Efficiency Standard (MEES) [21], and the UK government has an aspiration that all homes, where feasible, are EPC-C rated by 2035 [31]. The model underlying the EPC is also used in official fuel poverty statistics in England, whereby homes in bands A-C (inclusive) cannot be classed as fuel poor since their energy expenditure is expected to be low [6].

EPCs are not intended to give a prediction of the actual energy use of a particular home as they assume normative consumption. However, to be as effective as possible given their current uses, on average they should provide a reasonably accurate measure of the regulated energy use. This leads to our first research question:

- Is there a significant difference between metered primary energy use intensity (PEUI) and EPC-modelled PEUI?

Additionally, any systematic difference between metered and modelled energy use should be independent of the modelled energy use, ideally there should be a 1:1 linear relationship between EPC modelled and actual energy use. This leads to our second research question:

- What is the relationship between metered PEUI and EPC-modelled PEUI?

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E-mail address: jessica.few@ucl.ac.uk (J. Few).

https://doi.org/10.1016/j.enbuild.2023.113024

Few *et al.* (2023)

Diurnal/cyclical variation in energy use (profiles, cluster analysis)

Tom Rushby, University of Southampton

Martin Pullinger, University College London

Understanding Habitual Energy Use

Smart Energy Research Lab Consortium
End of Award Dissemination and Celebration

Tom Rushby & Ben Anderson
Energy and Climate Change Division
University of Southampton

6th December 2023

Contents

- What is habituality and why are we interested?
- Our approach
- Two methods
- Modelling results

What is habituality and why are interested?

- **habitual** (adjective) – done constantly or as a habit, regular, usual
- **habit** (noun) – a settled or regular tendency or practice

We really don't know:

- how temporally fixed or chaotic energy use is
- if habituality varies for different kinds of households

This matters for understanding and modelling flexibility

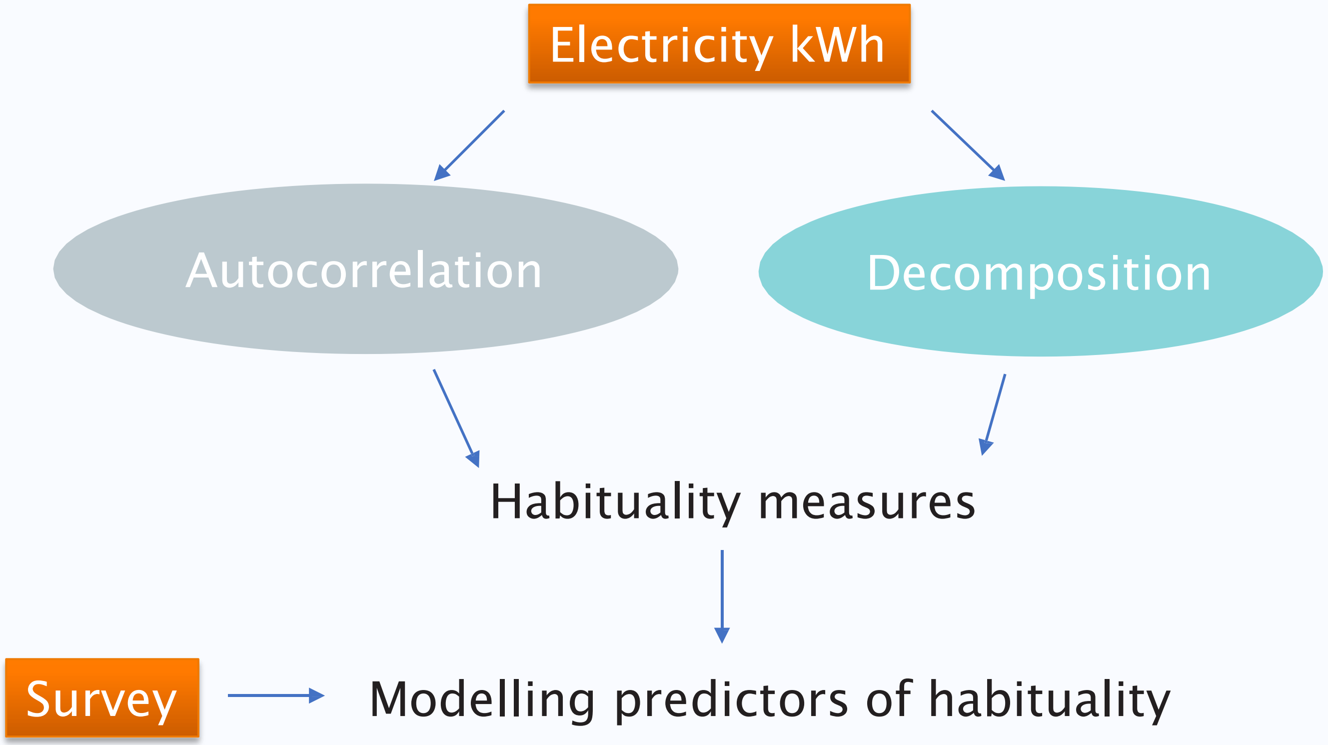
Our approach

Data selection

- Electricity demand
- Gas-heated
- N ~ 6-8k

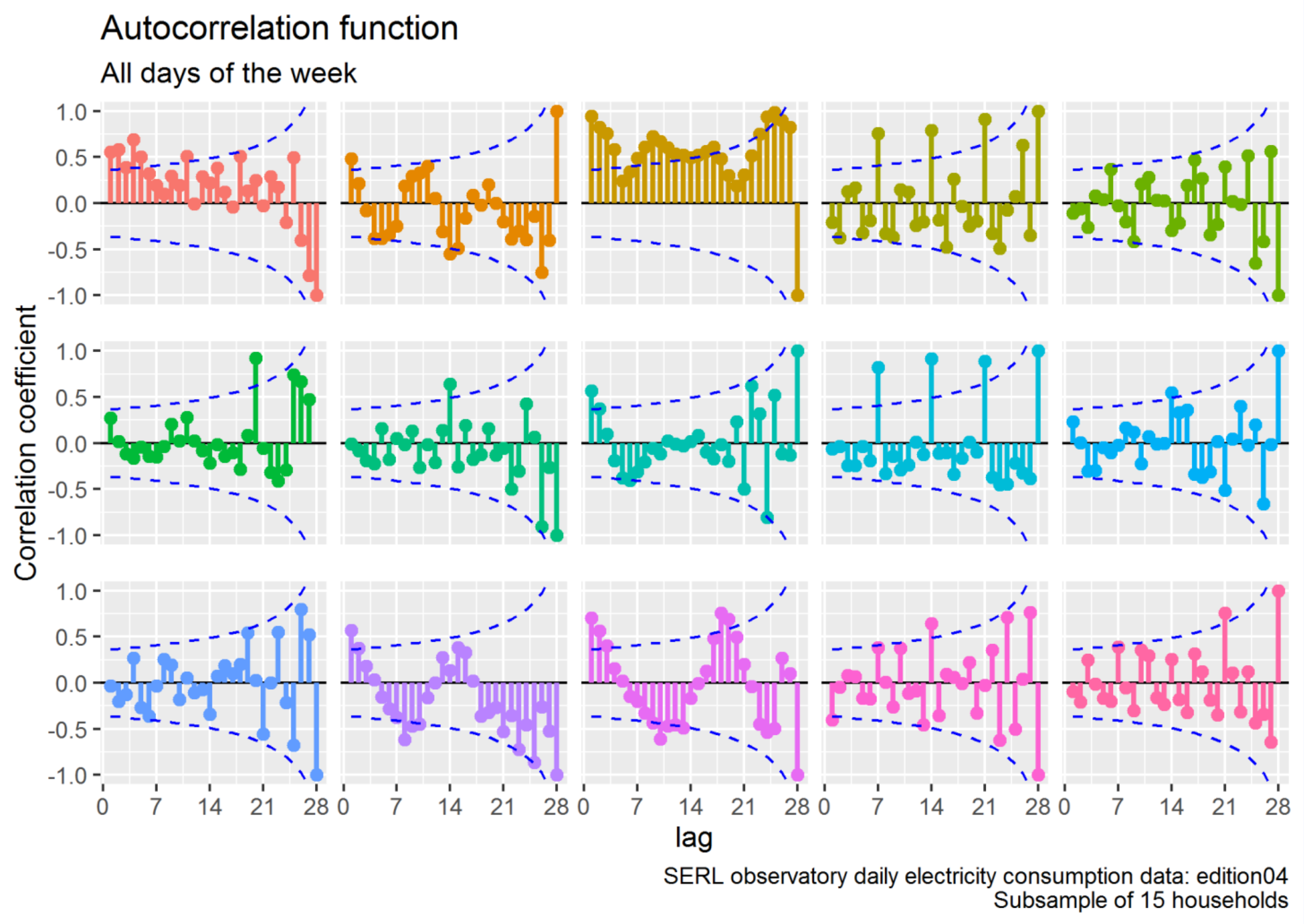
Two methods:

- Autocorrelation
- Decomposition



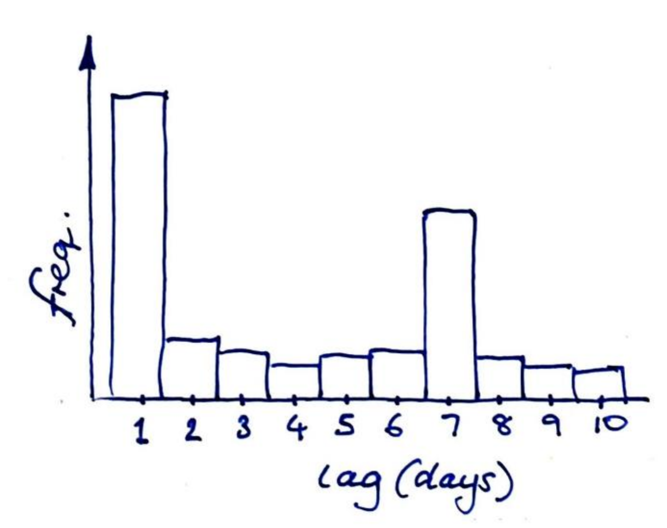
'Habituality' (1)

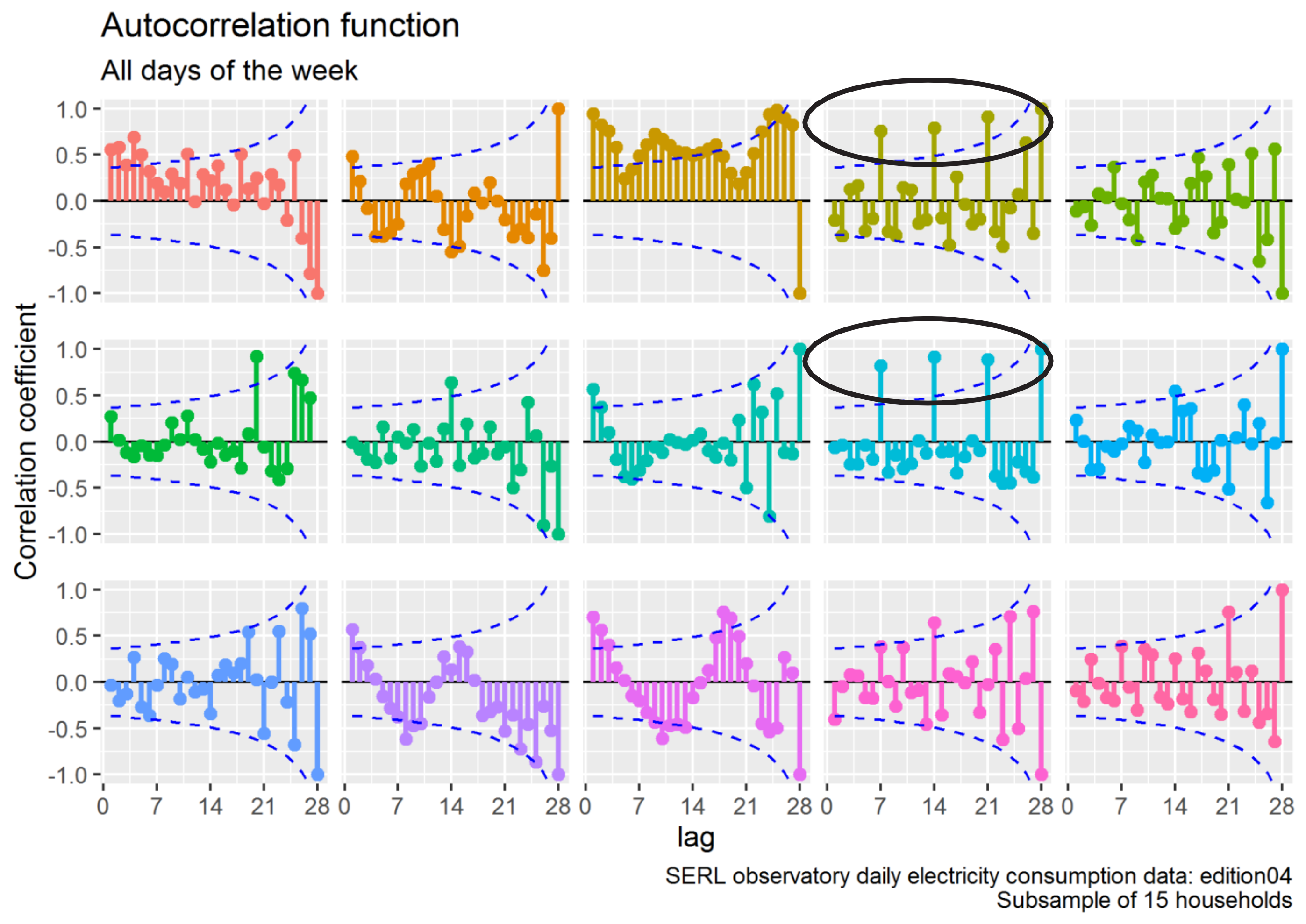
Autocorrelation



'Habituality' (1)

Autocorrelation

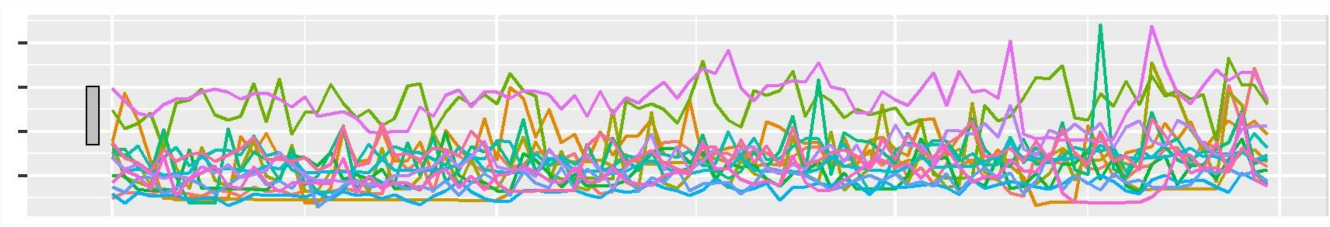




'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand

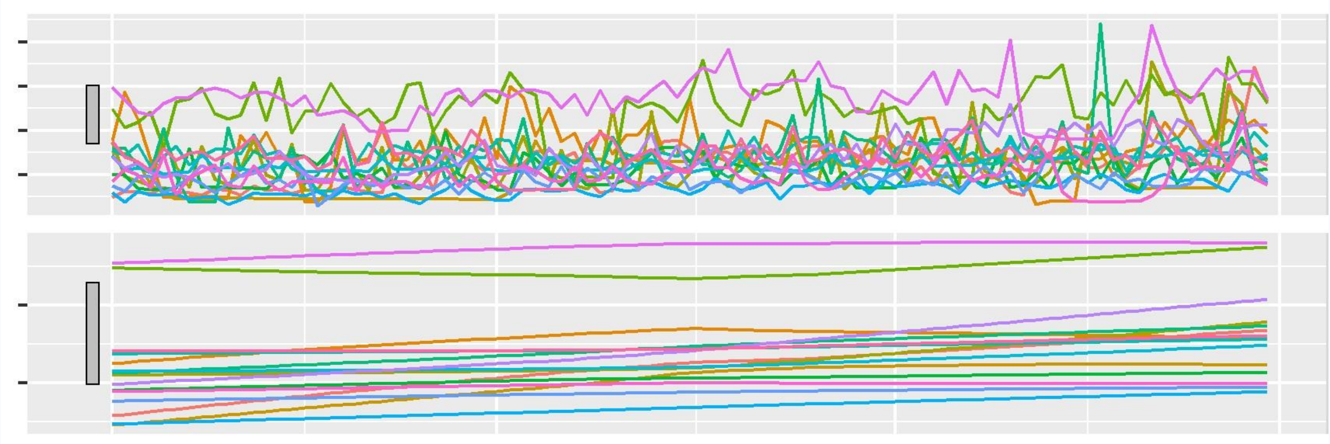


'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand:

Trend



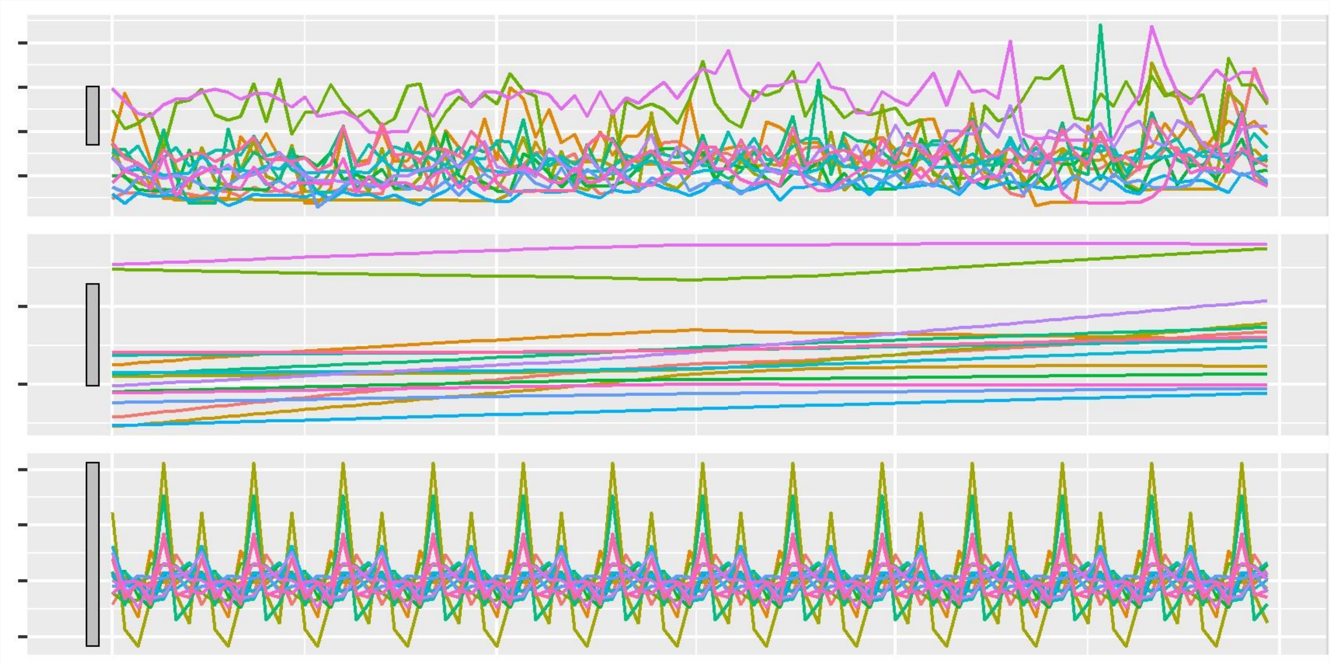
'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand:

Trend

+
Seasonal (weekly)



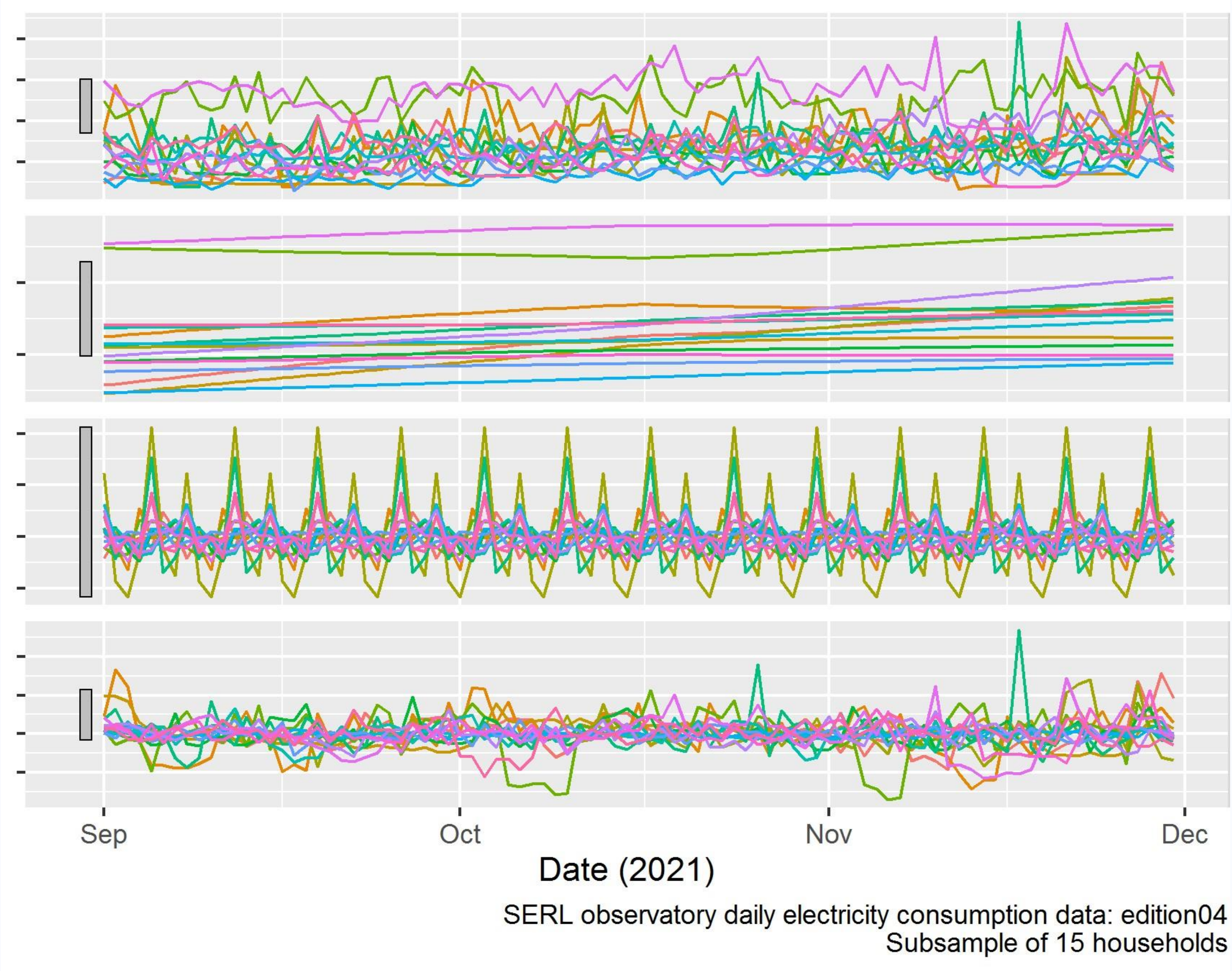
'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand:

Trend

+
Seasonal (weekly)
+
Residuals



'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand:

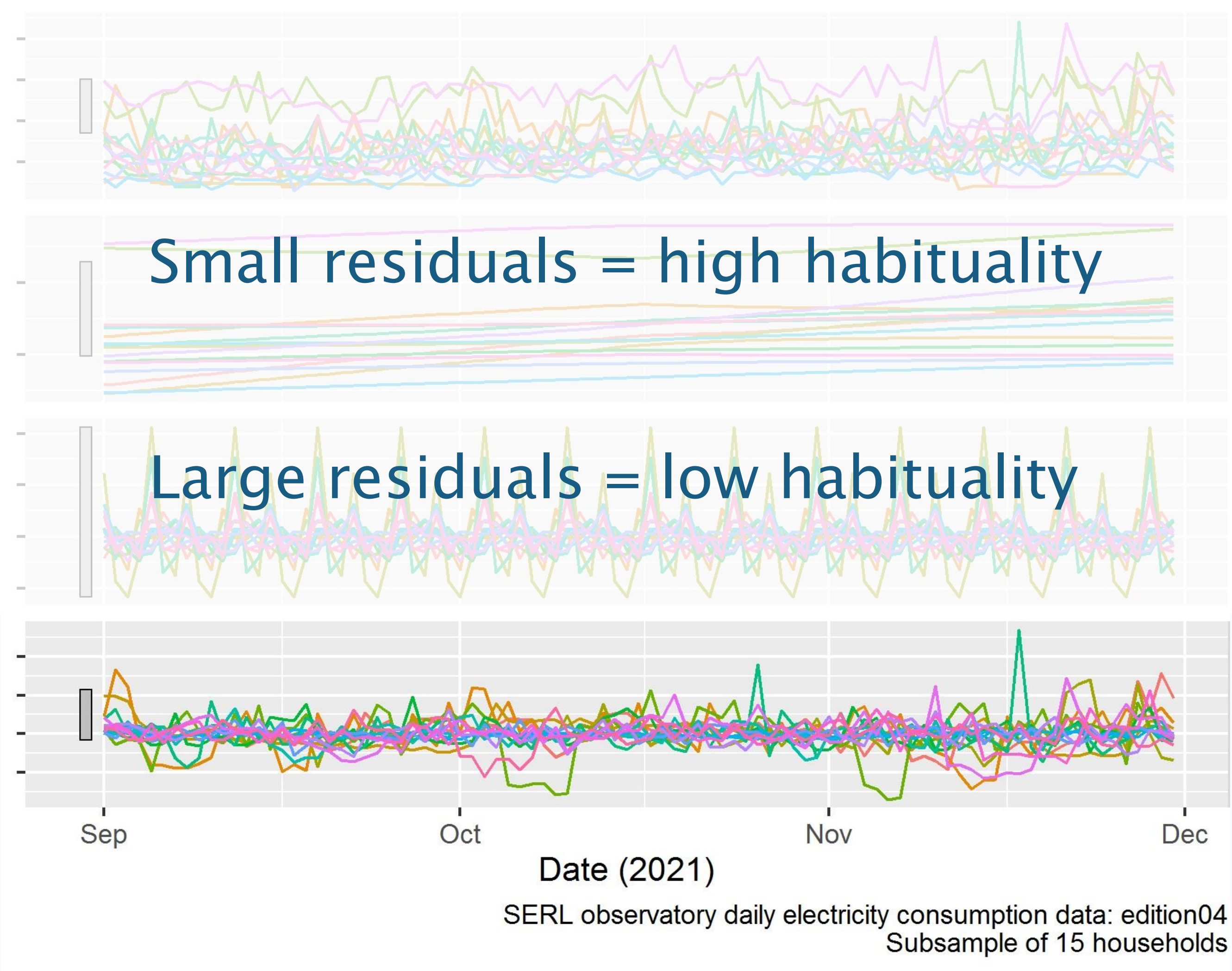
Trend

+

Seasonal (weekly)

+

Residuals



Modelling

Predictors:

- Household characteristics
- Appliance ownership

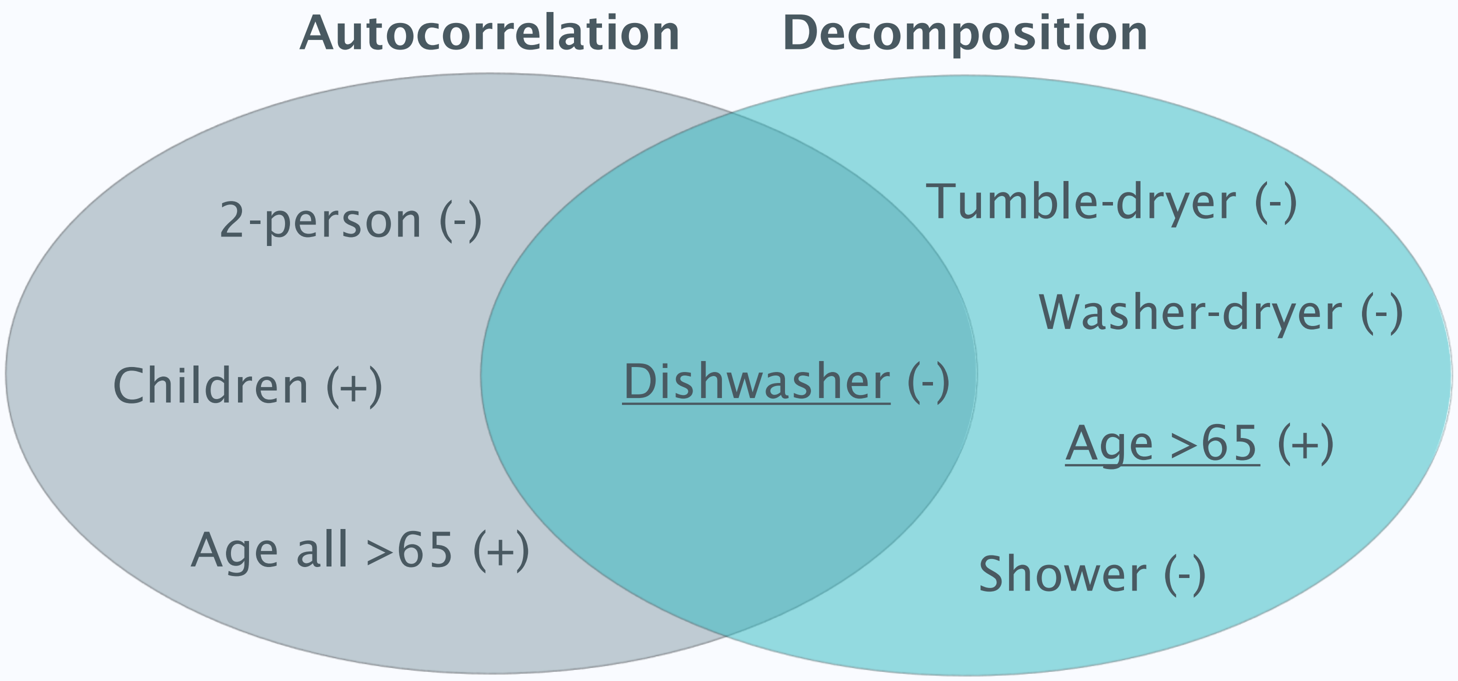
Data:

<table>
<tr><th>Method</th><th colspan="2">Sept - Oct 2021</th><th colspan="2">Nov – Dec 2021</th></tr>
<tr><td rowspan="2">Auto-correlation</td><td colspan="2">Daily total</td><td colspan="2">Daily total</td></tr>
<tr><td>a.m. peak</td><td>p.m. peak</td><td>a.m. peak</td><td>p.m. peak</td></tr>
<tr><td rowspan="2">Decomposition</td><td colspan="2">Daily total</td><td colspan="2">Daily total</td></tr>
<tr><td>a.m. peak</td><td>p.m. peak</td><td>a.m. peak</td><td>p.m. peak</td></tr>
</table>

Preliminary results *

Predictors:

- Household characteristics
- Appliance ownership



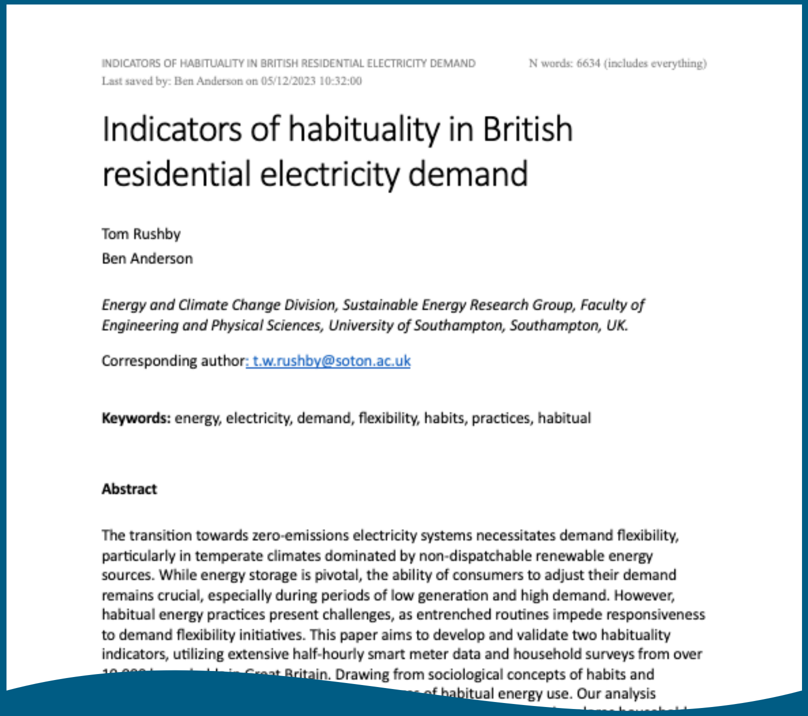
Next steps

SERL:

- Refinement of metrics/models
- Journal paper in preparation

Future:

- Re-analysis of flexibility trial data
- Covid as a natural experiment



INDICATORS OF HABITUALITY IN BRITISH RESIDENTIAL ELECTRICITY DEMAND N words: 6634 (includes everything)
Last saved by: Ben Anderson on 05/12/2023 10:32:00

Indicators of habituality in British residential electricity demand

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Ben Anderson

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Corresponding author: t.w.rushby@soton.ac.uk

Keywords: energy, electricity, demand, flexibility, habits, practices, habitual

Abstract

The transition towards zero-emissions electricity systems necessitates demand flexibility, particularly in temperate climates dominated by non-dispatchable renewable energy sources. While energy storage is pivotal, the ability of consumers to adjust their demand remains crucial, especially during periods of low generation and high demand. However, habitual energy practices present challenges, as entrenched routines impede responsiveness to demand flexibility initiatives. This paper aims to develop and validate two habituality indicators, utilizing extensive half-hourly smart meter data and household surveys from over

Thanks for listening!

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https://energy.soton.ac.uk/serl/

Archetypes of energy demand profiles
Change over time

Martin Pullinger

SERL Consortium End of Award event

6 December 2023

UCL
THE UNIVERSITY of EDINBURGH
SMART ENERGY RESEARCH LAB
UNIVERSITY RESEARCH FOR PUBLIC GOOD

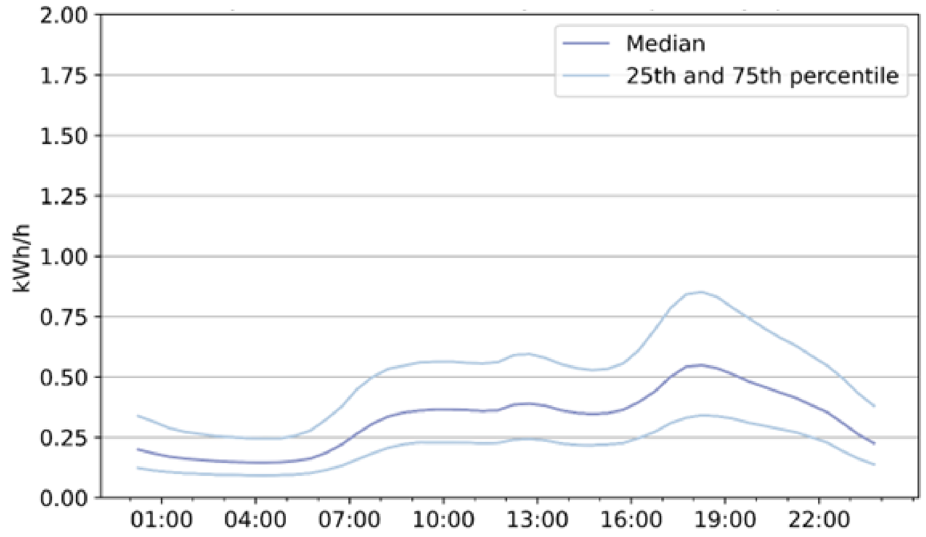
Scope of presentation

- Starting point and aims
- Methodology
- Selected results

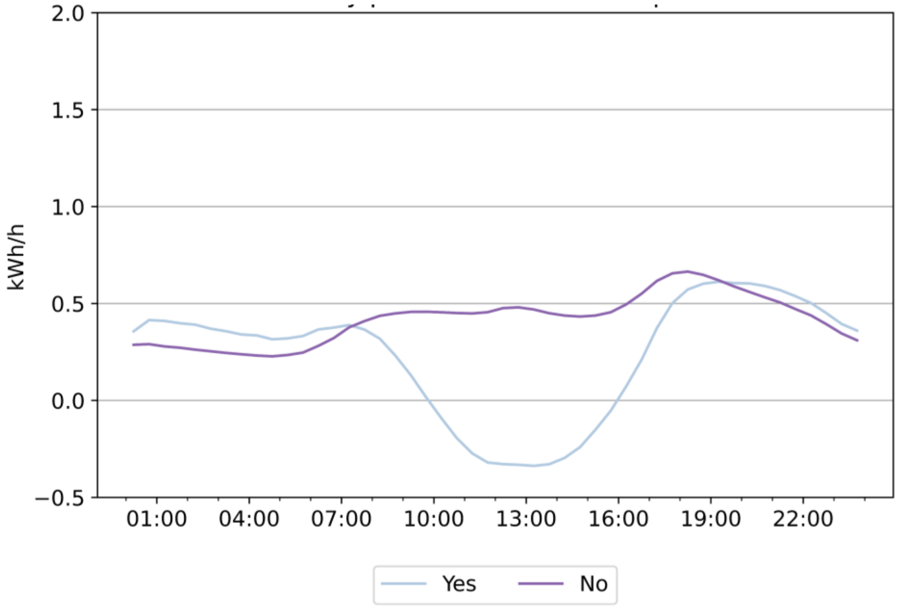
Starting point and aims

- Averages demand profiles… … vary between groups

Electricity, full sample, 2021



Electricity, full sample, 2021, by PV ownership



- SERL Observatory is a rich resource for:
  - identifying common 'archetypes' of demand profile,
  - investigating how they change in prevalence over time and by household type

Figures reproduced from Few et al 2021 Smart Energy Research Lab: Energy use in GB domestic buildings 2021

Methodology

Input data

- Half-hourly smart meter data
- Electricity and gas
- 13,000 homes, Great Britain
- September 2019-August 2022

Archetype generation

- Clean data
- Downsample to 2-hour resolution, normalise
- K-means++ cluster analysis
- Name each cluster

Outputs

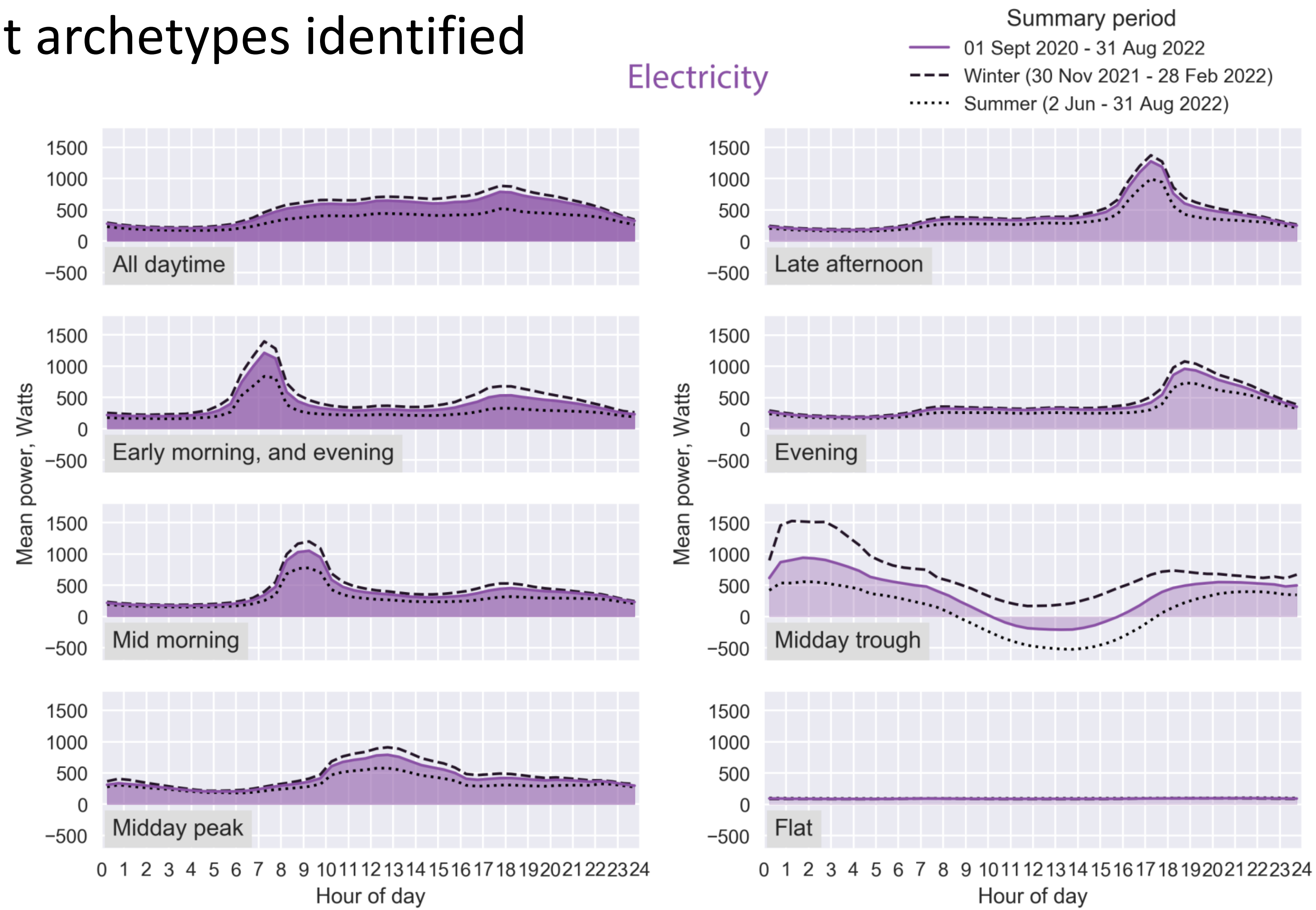
- Archetype labels for each day per home and per fuel

Analyses

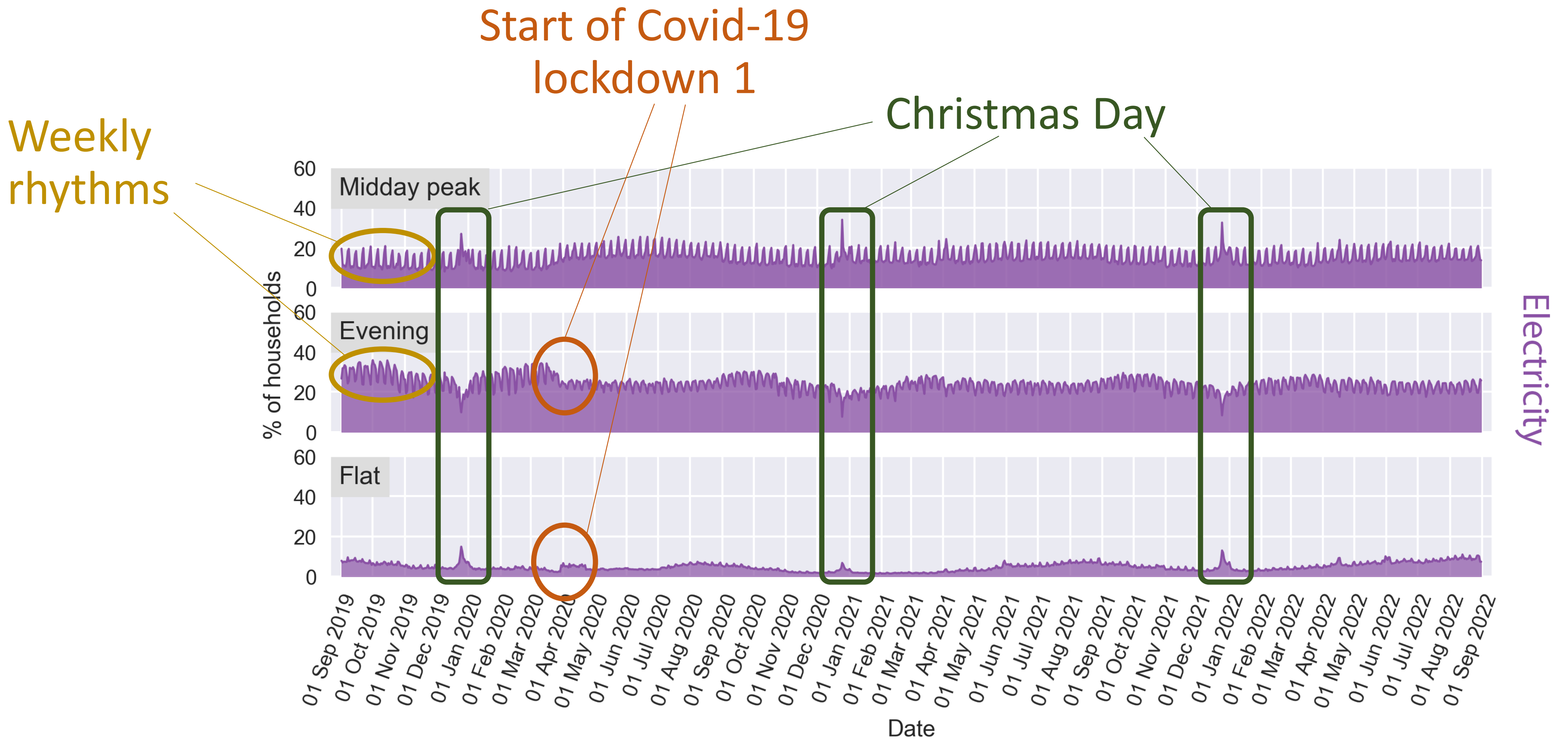
- Archetype characteristics
- Variation in prevalence over time

Characteristics of the archetypes

- **Eight archetypes identified**

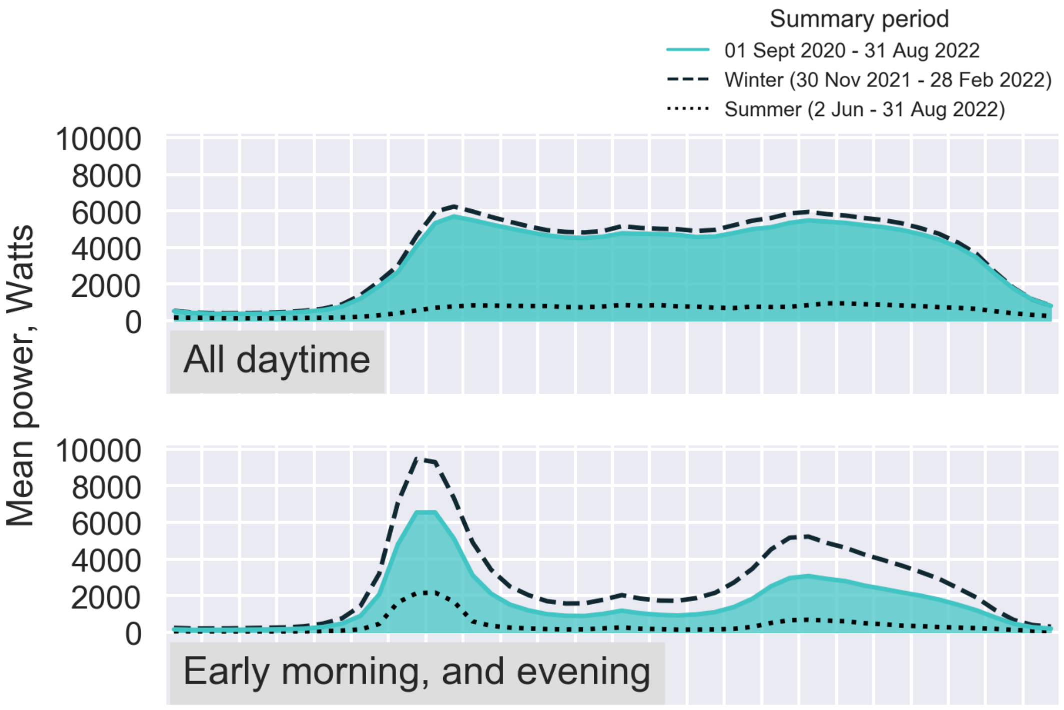


Archetype prevalence varies over time

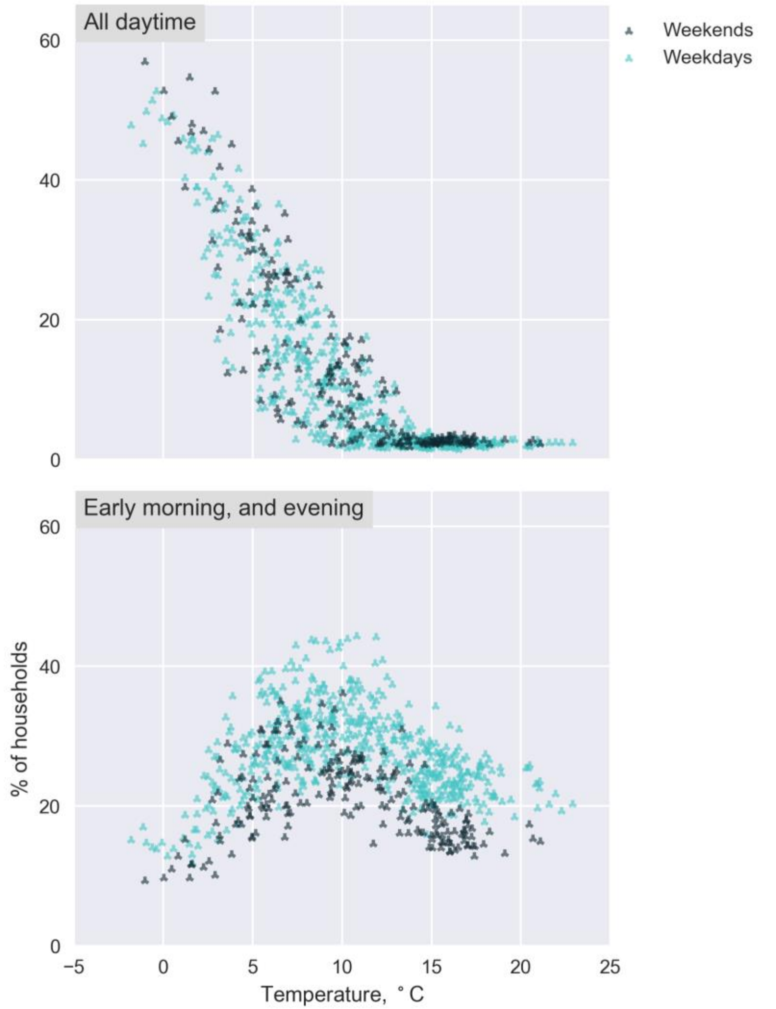


Prevalence varies with external temperature (via heating)

Gas mean profiles for two archetypes, full sample



Variation of prevalence of the two archetypes across all homes with gas central heating, July 2020 – June 2022



Next steps

Ongoing

- Journal article:
  - Pullinger, Zapata-Webborn, Kilgour et al (2023) *Capturing variation in daily energy demand profiles over time with cluster analysis in British homes (September 2019 – August 2022).*
  - Preprint: OSF. DOI: 10.31219/osf.io/ckyb6
  - Forthcoming: Applied Energy (accepted pending minor revisions)

- Second article on relationship between demand archetypes and household characteristics

Possible future work

- How do archetypes vary over winter 2022/23 and 23/24?

Break

Regional energy use (Welsh/Scottish/regional results)

Martin Pullinger, UCL + University of Edinburgh

Simon Lannon, University of Cardiff

The Scotland Government's 'Just Transition'

The current situation of homes in Scotland: DEDEUS project

Martin Pullinger

SERL Consortium End of Award event

6 December 2023

THE UNIVERSITY of EDINBURGH

UCL

SMART ENERGY RESEARCH LAB
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Starting point: Scottish Government strategy*

Targets

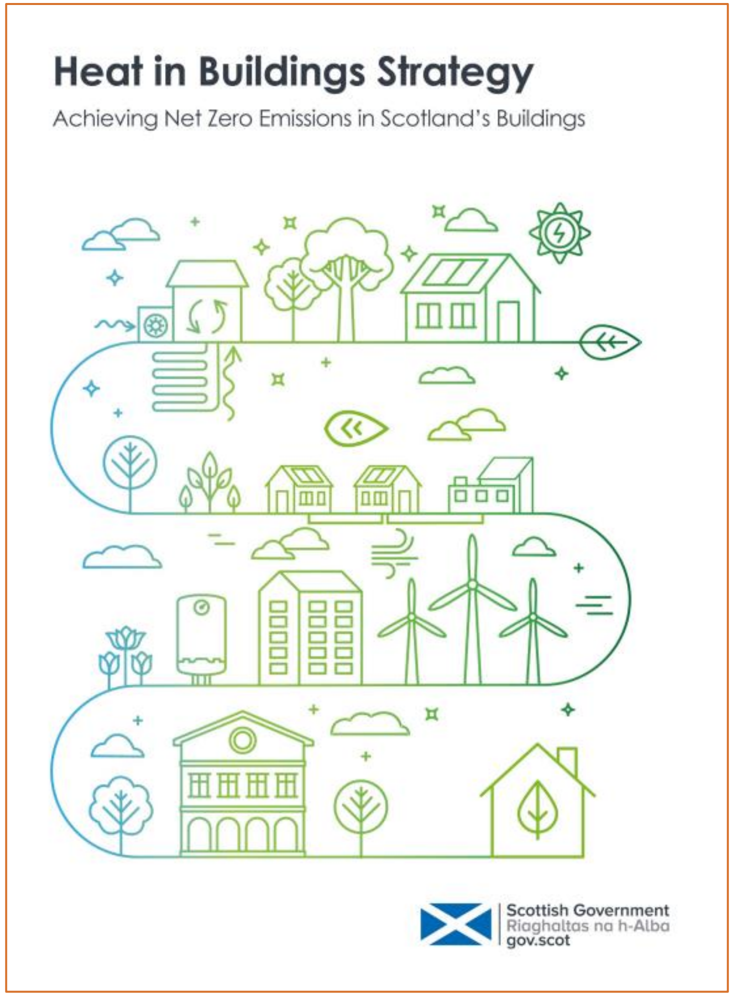
- All homes EPC band C by 2033 (band B for social housing by 2032)

  "where technically and legally feasible"

- Reduce fuel poverty to below 5% of households by 2040

Approach

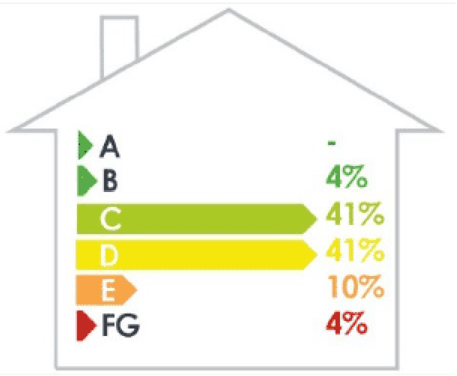
- 'Fabric first' approach: improved building envelope
- Transition to 'zero direct emissions' heating – heat pumps, district heating; no fossil fuels or biofuels.

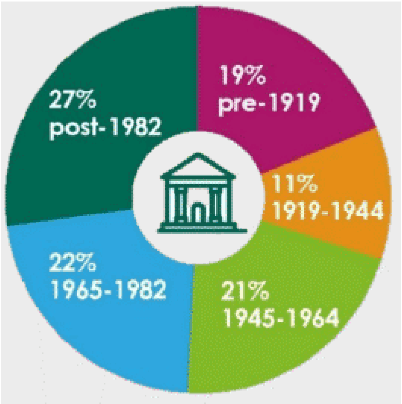


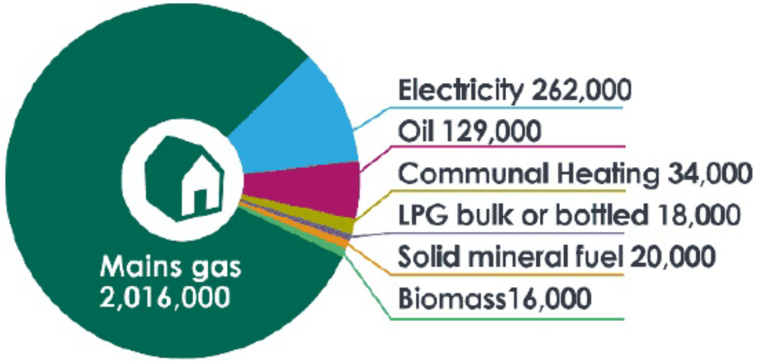
* (2021) Housing to 2040 Strategy; (2021) Heat in Buildings Strategy

Context

- Energy performance: 55% of homes below EPC C
- 19.5% households in fuel poverty (9.5% in extreme fuel poverty) (SHCS 2021*)
- Several challenging domestic building types
    - Off-gas-grid homes with high emissions heating fuels (oil, LPG, solid) ~180,000 (7%)
    - Traditional and heritage buildings ~19% (pre-1919)
    - Mixed tenure and mixed-use ~35% (tenements, other flats)







Refs: Scottish House Condition Survey, 2019, cited in Scottish Government, 2021, Heat in Buildings Strategy. https://www.gov.scot/publications/heat-buildings-strategy-achieving-net-zero-emissions-scotlands-buildings/
SHCS 2021: https://www.gov.scot/publications/scottish-house-condition-survey-2021-key-findings/pages/3-fuel-poverty/

Project aims

To address the questions:

What is the current situation of Scottish households in terms of…

- Heating technologies
- Occupant characteristics
- Location
- Energy demand patterns
- Wellbeing outcomes – ability to heat home, damp problems
- Capabilities to pay for retrofits – financial, ownership

How does this vary between the different household groups that are treated separately in Scotland’s housing strategy?

Project approach

Interim policy brief

- Energy demand patterns for selected groups of households

Policymaker engagement

- Feedback on additional analyses

Refine analyses

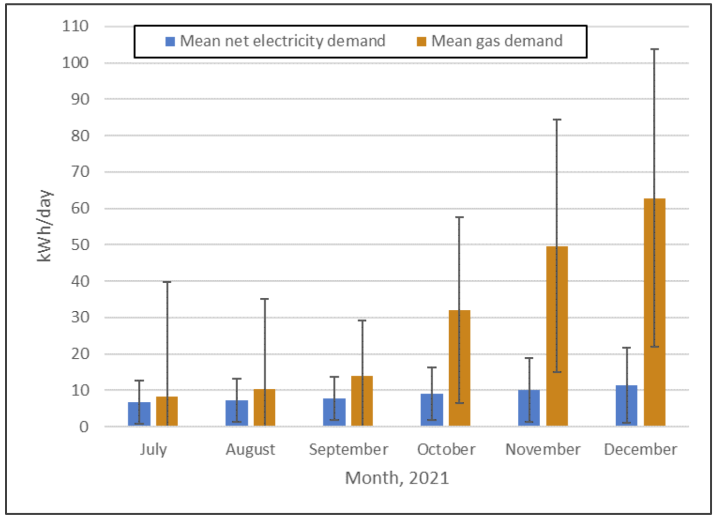
- Ground in SG feedback, strategy
- Update with more recent data

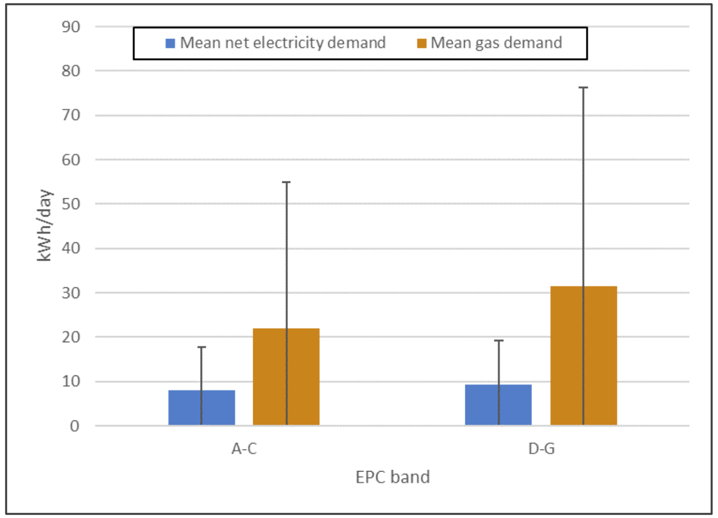
Dissemination

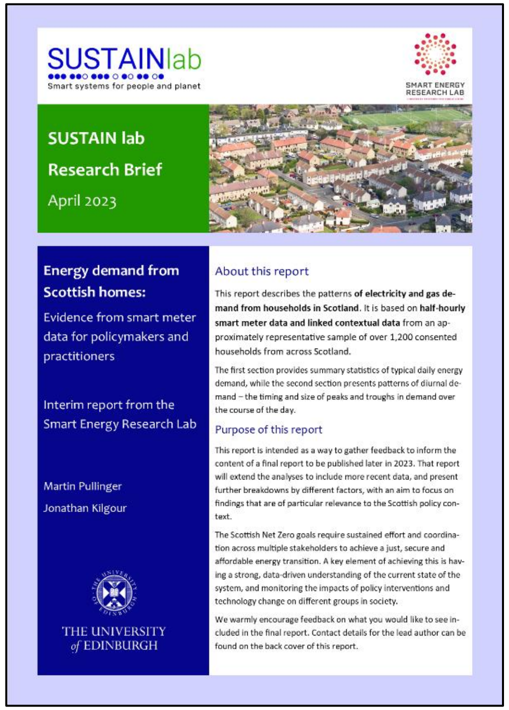
- Journal article
- Final policy brief

Outputs to date: Interim research brief

- Daily mean energy use and demand profiles for H2 2021, different segmentations
  - DOI: [10.31219/osf.io/b8wu9](https://doi.org/10.31219/osf.io/b8wu9)





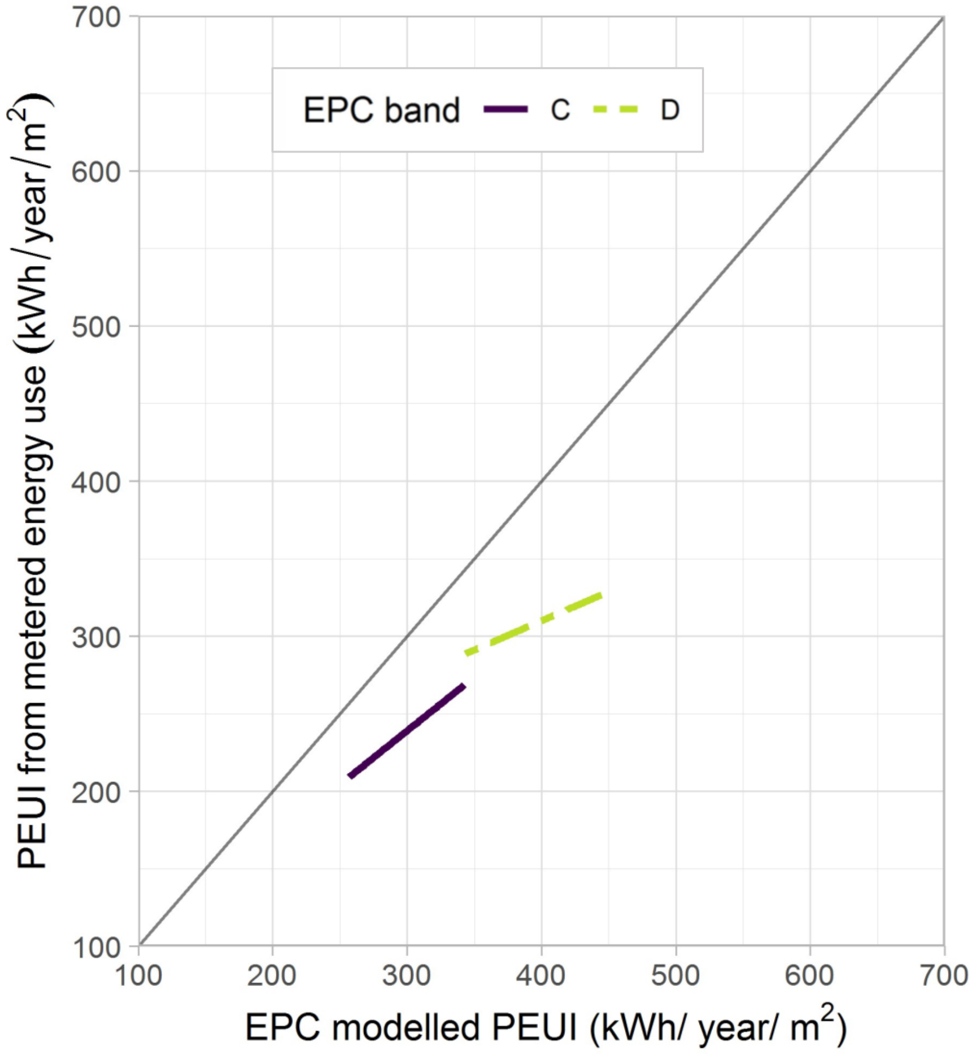


- Policymaker engagement Q2 2023:
  - Feedback gathered to shape final research aims and outputs
    -> Include EUI, energy use per occupant, more recent data

Outputs to date: EPC analysis

- Home's EPC rating is key targeting tool in SG strategy
- SERL participants' primary energy use intensity (PEUI) is below that predicted by EPCs
- Sufficient data only for analysis of EPC bands C and D
- Follows similar pattern to results in Few et al 2023* for England and Wales (same Observatory dataset and methodology)

Gas centrally heated homes, no unmetered heating, no EV



*Few, Manouseli et al (2023) *The overprediction of energy use in Great Britain*, Energy and Buildings

Next steps

- Journal article on the current status of household segments in Scotland’s buildings strategy
  - Updated energy demand patterns (2022 data)
  - Wellbeing outcomes
  - EPC analysis
  - Target: Energy Policy, Q1 2024 submission

- Final report to SG policymakers
  - Greater range of energy statistics

Social Housing Research on Energy from Welsh Data (SHREWD)

Smart Energy Research Lab project 2020 to 2023

06.12.2023

Simon Lannon, Elaine Robinson, Bhawana Gupta, Rawan Jafar, Chris Tweed

SMART ENERGY RESEARCH LAB

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PRIFYSGOL CAERDYDD

SHREWD Aims and objectives

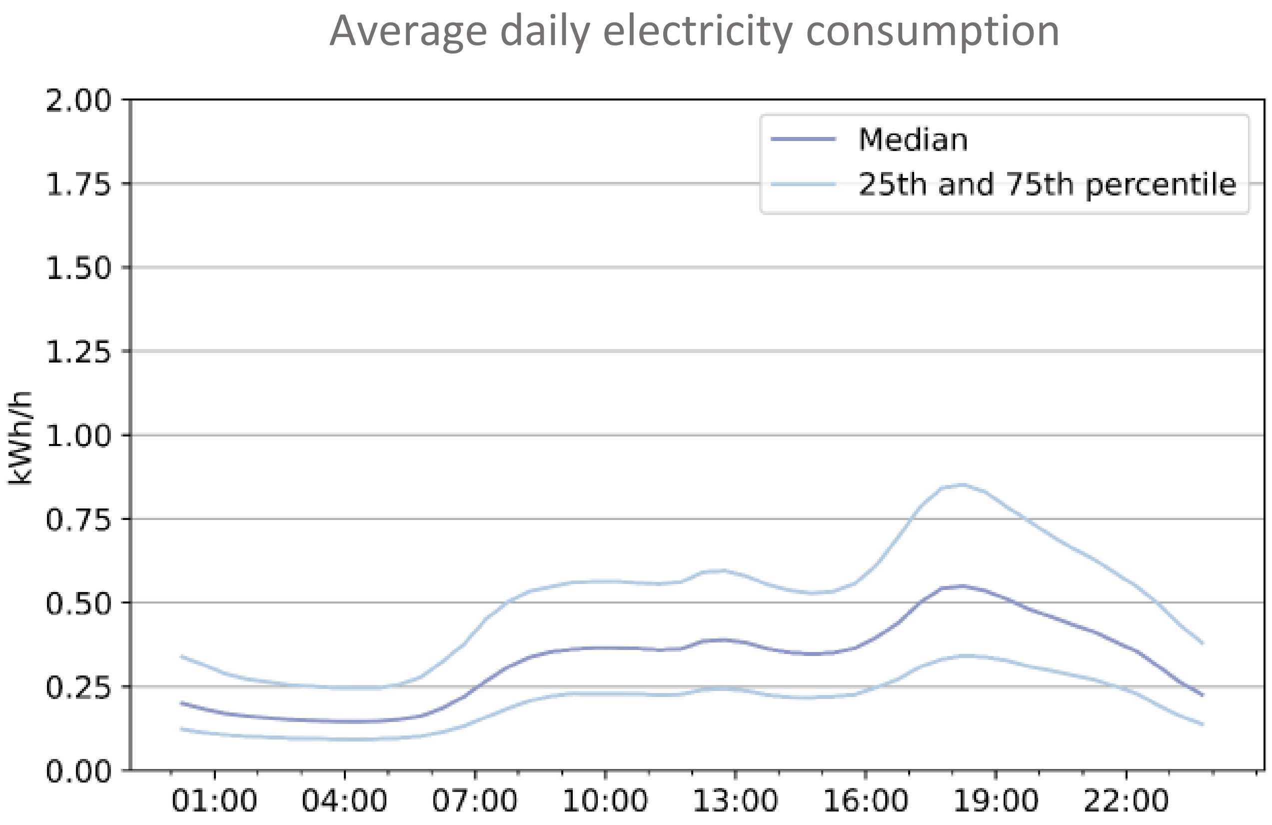
The project will use the SERL portal to collect Smart meter data and undertake analysis of the meter readings.

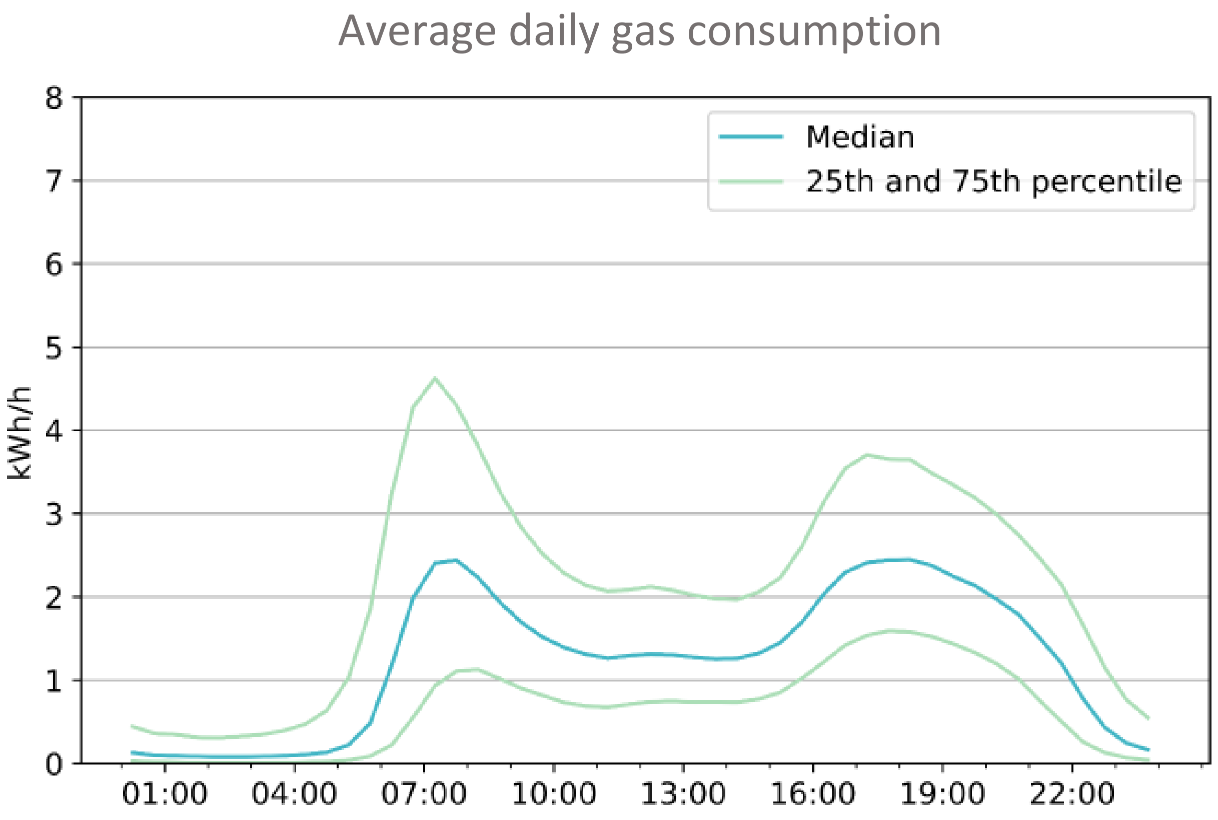
The overall aim is to understand the impact of housing policies can on energy consumption in Welsh social landlord dwellings.

There are five research objectives:

1. Working with 5 Landlords to establish a Welsh social housing energy observatory (SHREWD).
2. To collect detailed data on housing interventions from social landlords and other sources.
3. To explore the impact of these interventions on the energy consumption of dwellings.
4. To identify best practice by engaging with social landlords.
5. To disseminate findings for future energy efficiency policy and develop further data linkage methods.

SERL results - Energy use in GB domestic buildings 2021

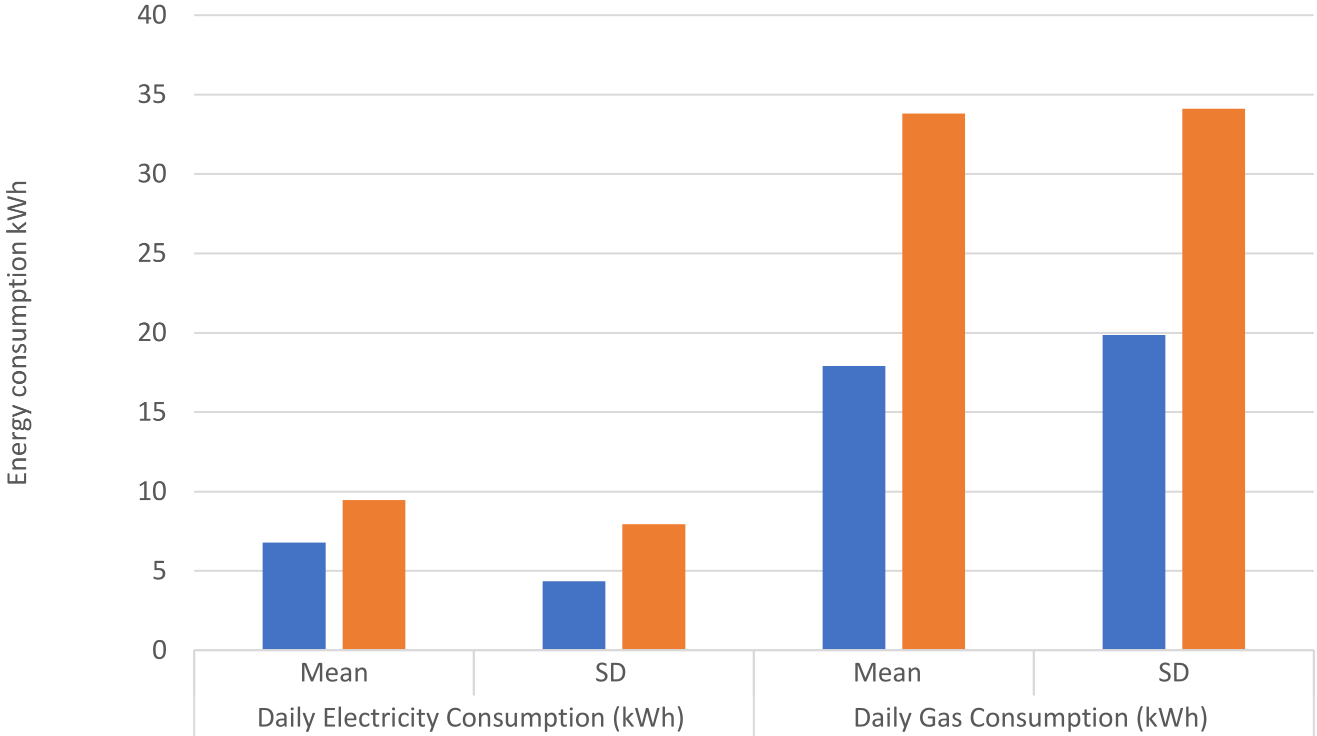




Smart Energy Research Lab: Energy use in GB domestic buildings 2021

SHREWD vs Welsh SERL energy results

Comparison of SERL daily electricity and gas consumption (Wales only) with SHREWD data

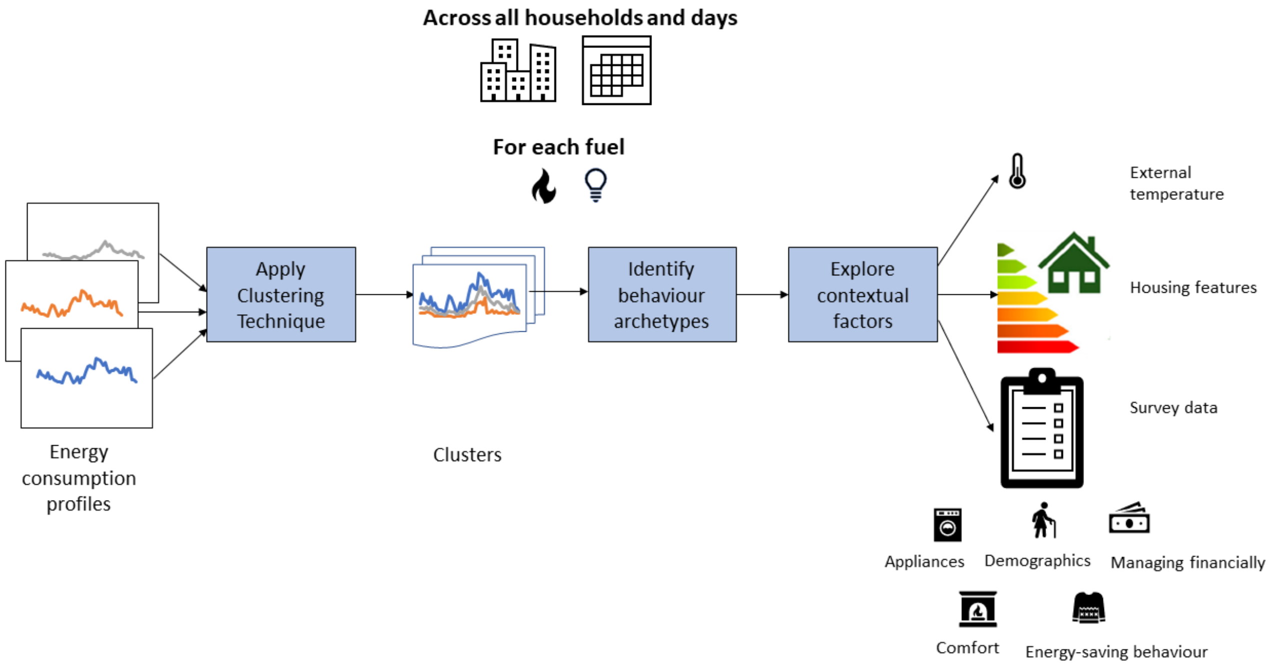


	Daily Electricity Consumption (kWh)		Daily Gas Consumption (kWh)	
	Mean	SD	Mean	SD
SHREWD	6.78	4.35	17.92	19.86
Welsh SERL	9.47	7.93	33.8	34.1

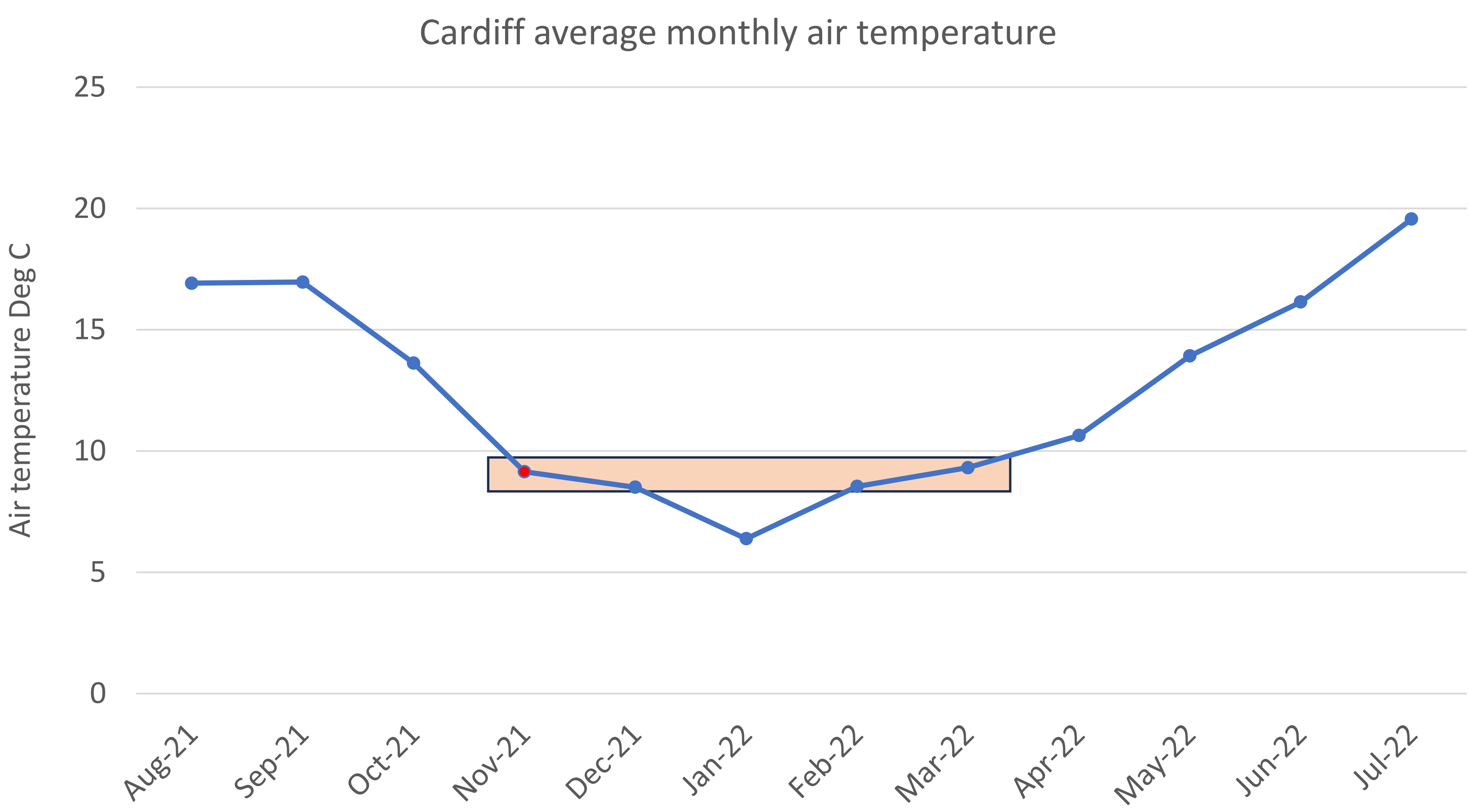
SHREWD Welsh SERL

SHREWD Cluster analysis method

- Gas and electricity use are analysed separately
- Daily profiles of energy use at half-hourly intervals are analysed using agglomerative clustering technique.
- Energy use is normalised by floor area from EPC data.
- Only those energy meter readings that have a valid read time are included:
  this is where the daily readings are the same as the sum of the half hourly readings



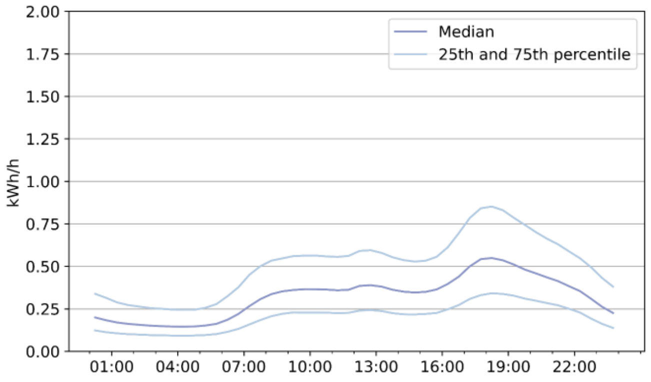
SHREWD weather data



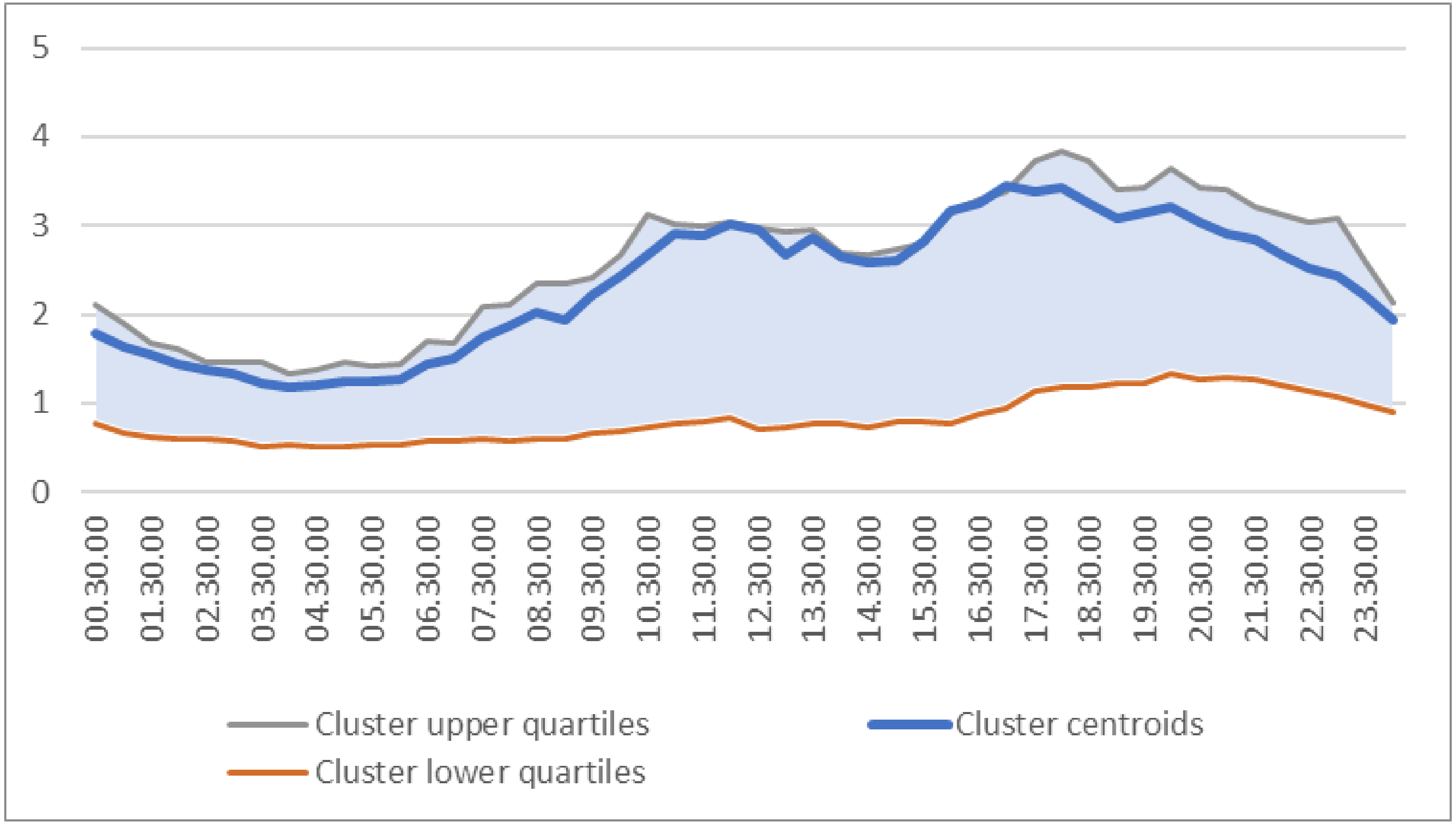
Daily profile

Electricity

November 2021



SERL data



Electricity, all clusters combined (n=975) (Wh/m2)

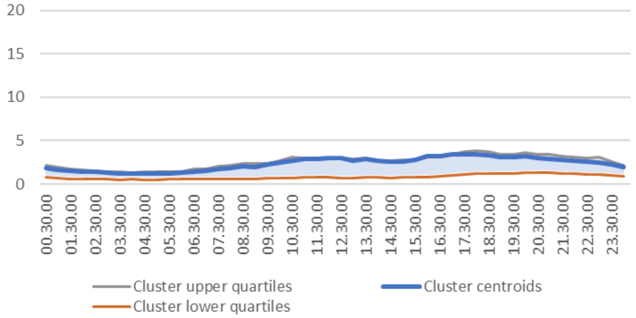
Cluster analysis results

Electricity

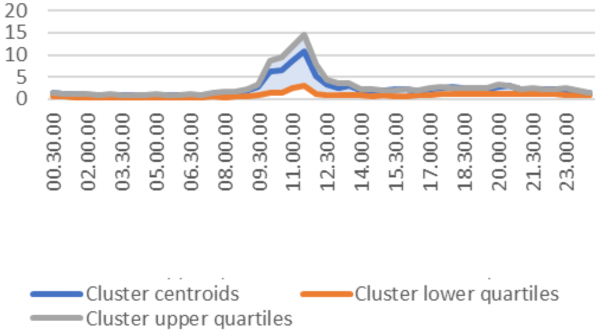
November 2021

All data (Wh/m2)

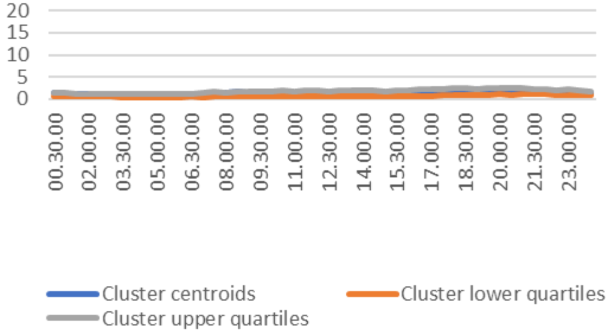
Nov-21, Electricity, all clusters (n=975)



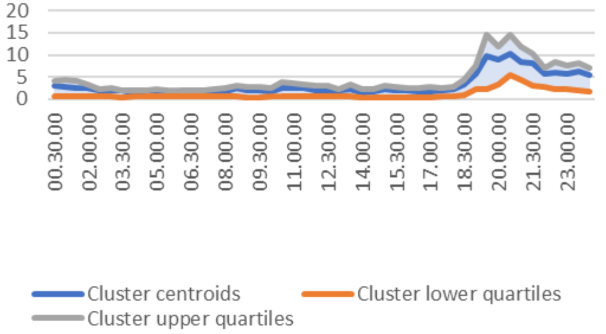
Nov-21, Electricity, cluster 1 (n=72)



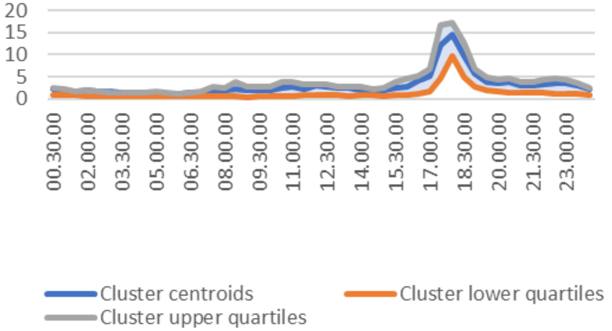
Nov-21, Electricity, cluster 2 (n=580)



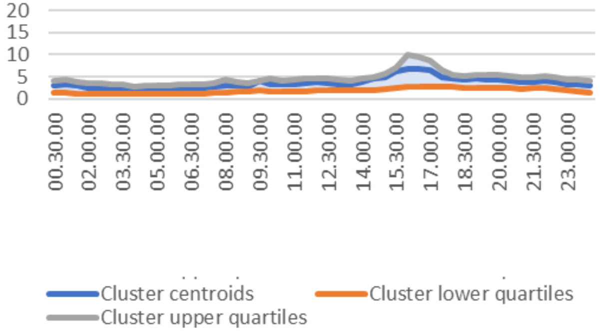
Nov-21, Electricity, cluster 3 (n=44)



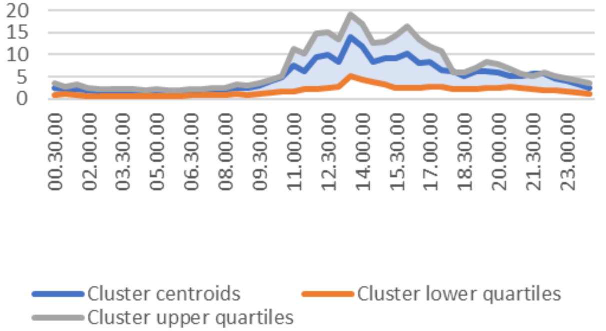
Nov-21, Electricity, cluster 4 (n=51)



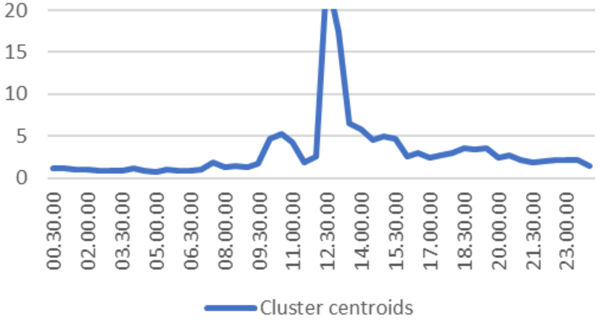
Nov-21, Electricity, cluster 5 (n=123)



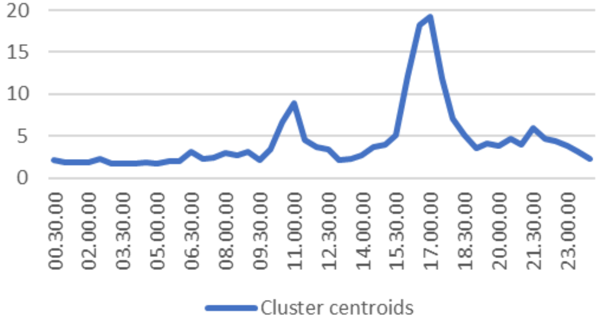
Nov-21, Electricity, cluster 6 (n=48)



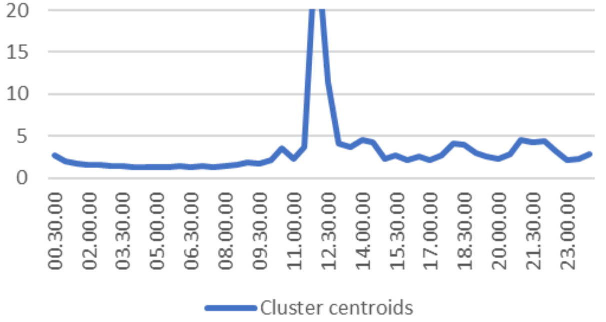
Nov-21, Electricity, cluster 7 (n=14)



Nov-21, Electricity, cluster 8 (n=24)



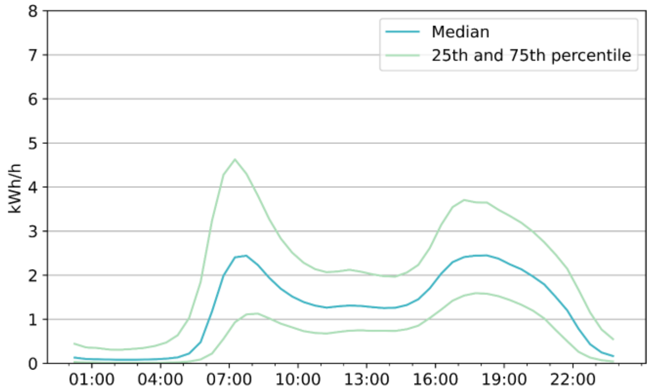
Nov-21, Electricity, cluster 10 (n=11)



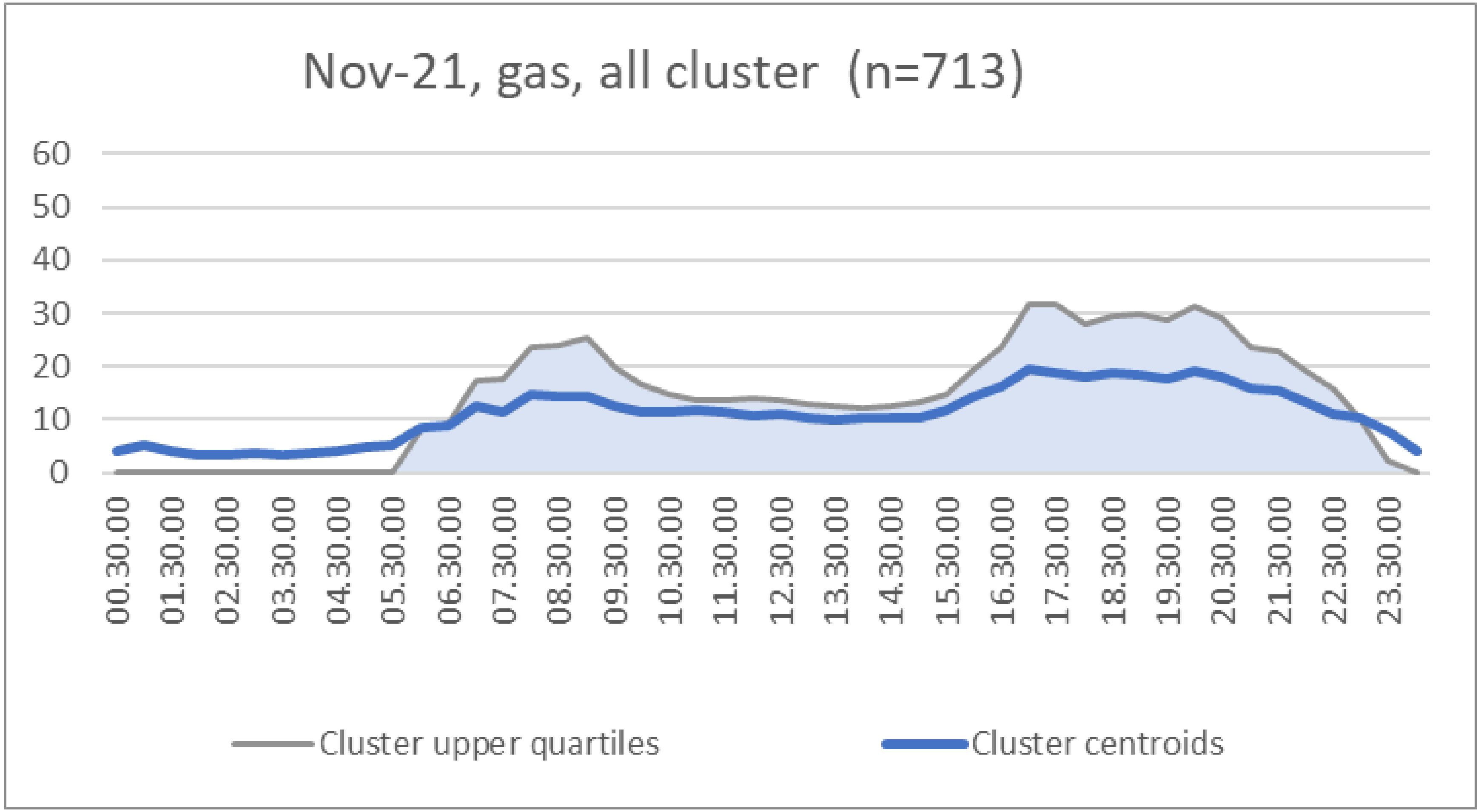
Daily profile

Gas

November 2021



SERL data

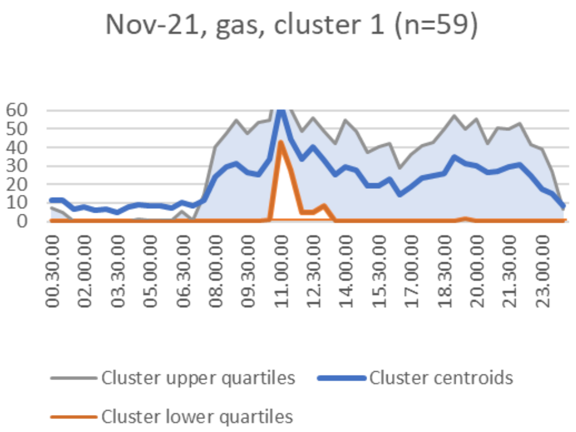


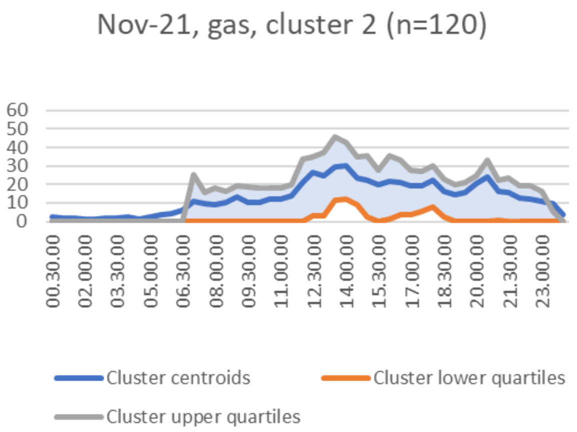
Gas, all clusters combined (n=713) (Wh/m2)

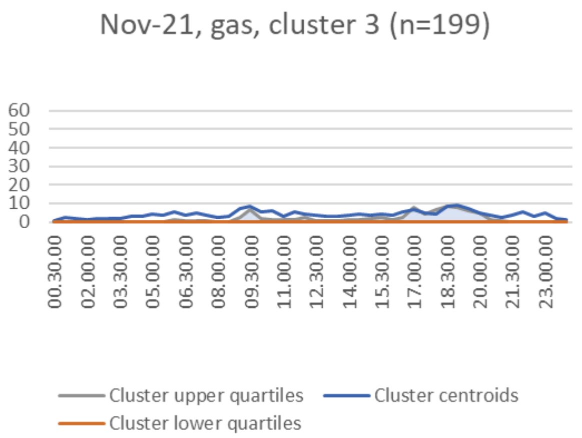
Cluster analysis results

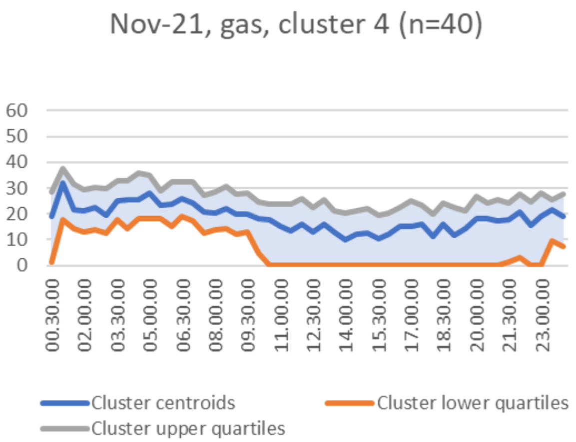
Gas

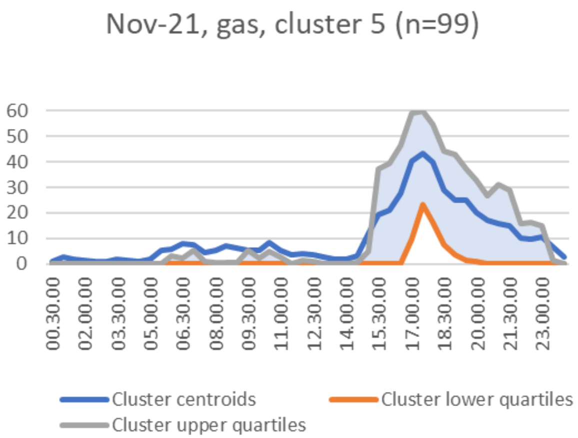
November 2021

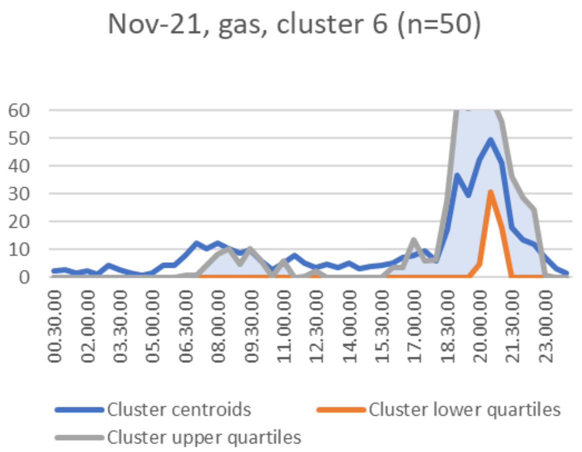




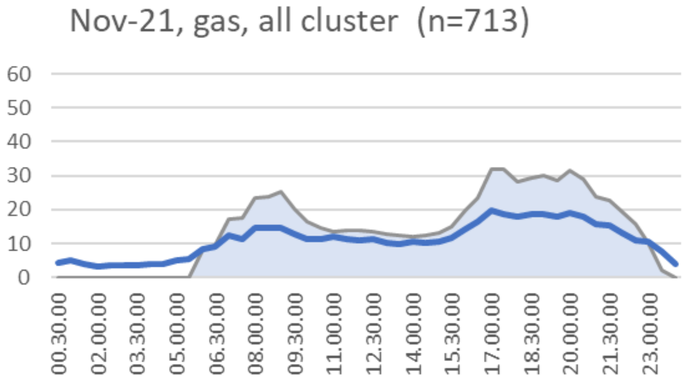


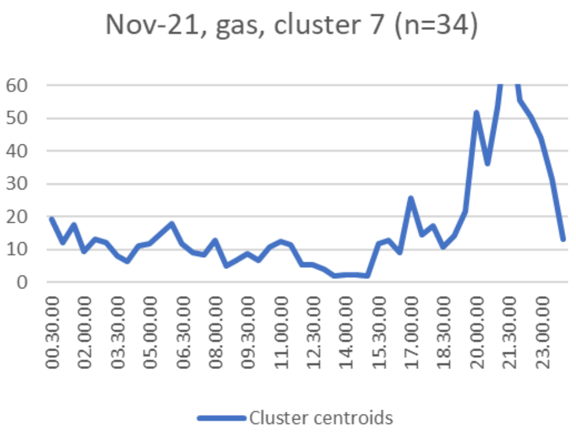


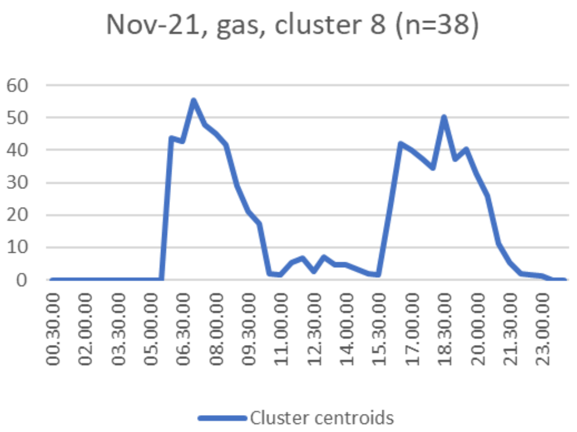


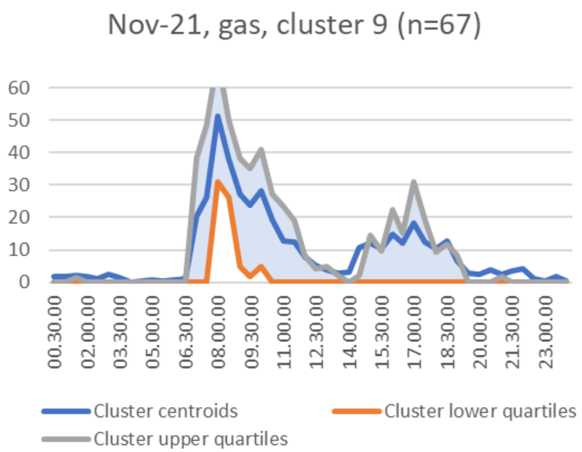


All data (Wh/m2)

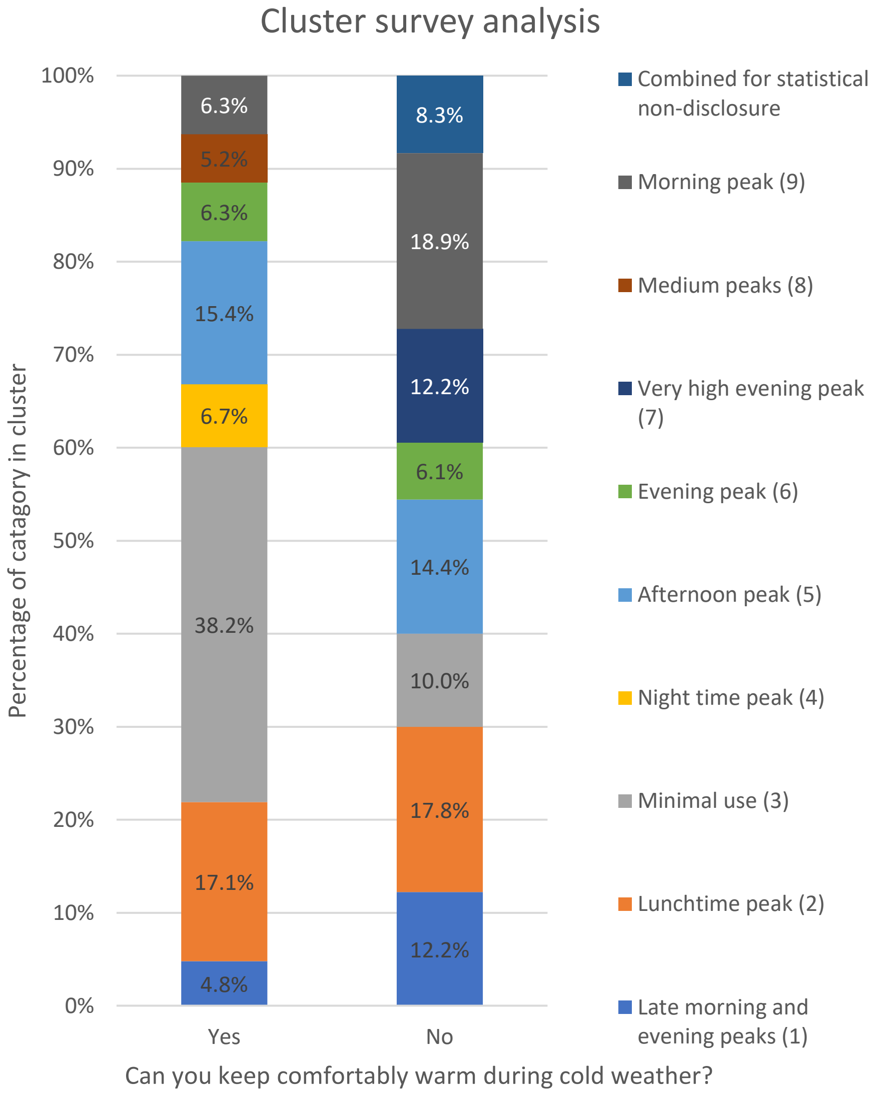








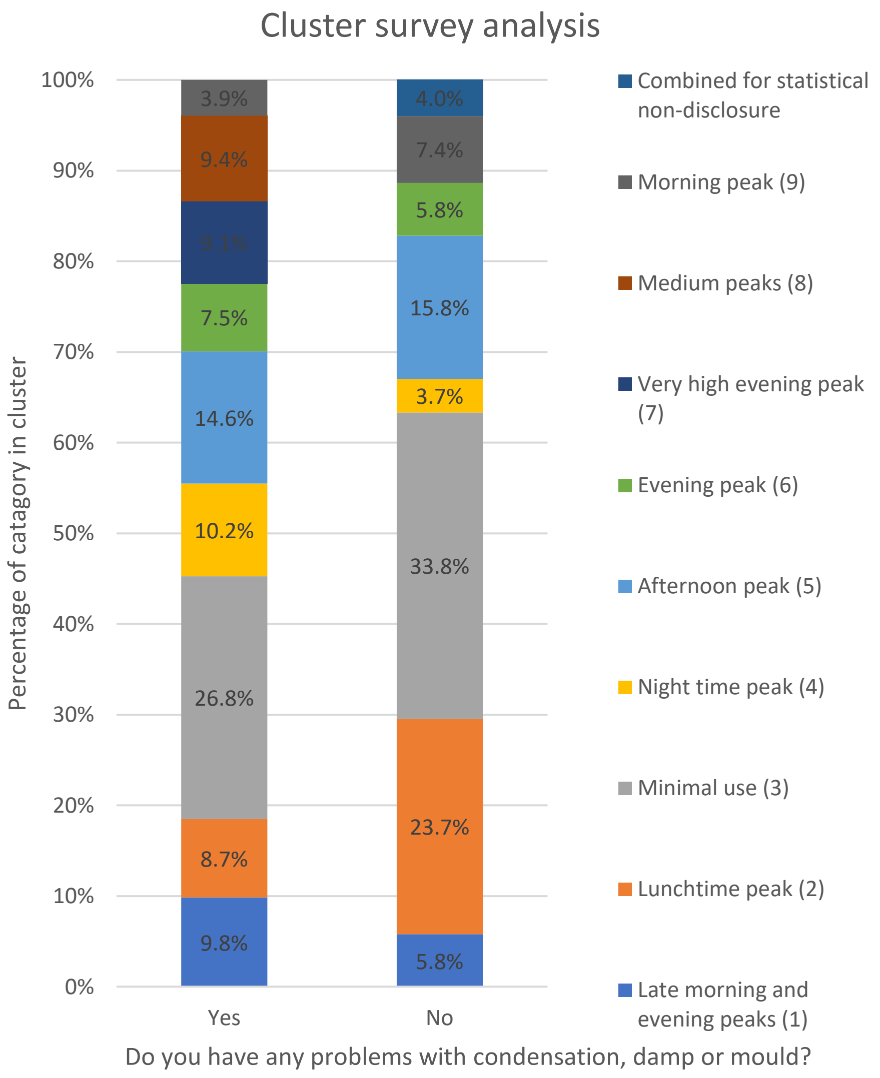
SHREWD Gas use Cluster and survey results - comfort



Minimal use cluster is more common with tenants that say they **can** keep comfortable

Late morning and evening peaks cluster or **morning peak cluster** or **very high evening peak** is more common with tenants that say they **can't** keep comfortable

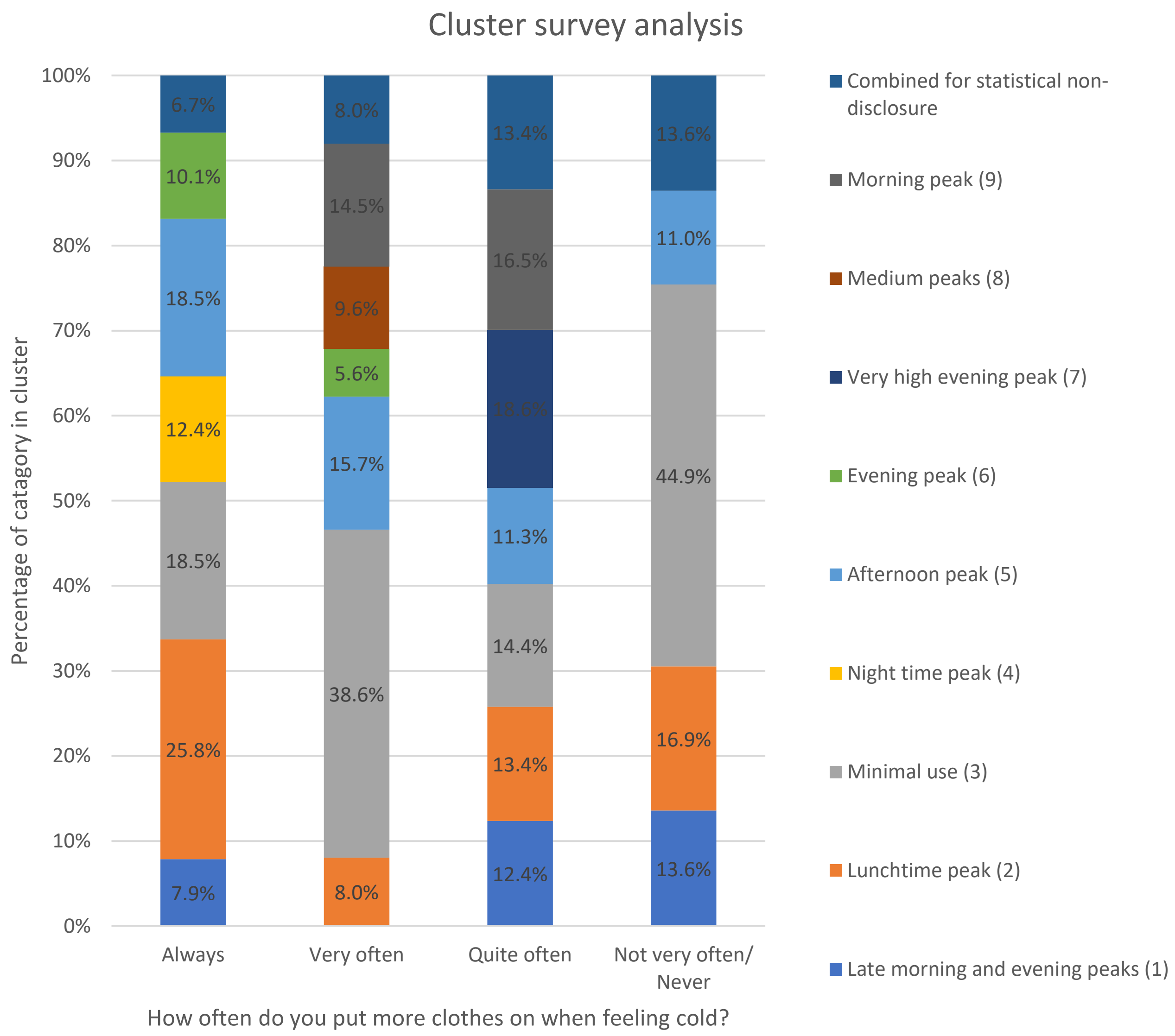
SHREWD Gas Cluster and survey results - damp



Lunchtime peak cluster or very high evening peak is more common with tenants that say they **don't** have damp problem

Late morning and evening peaks cluster is more common with tenants that say they **do** have damp problem

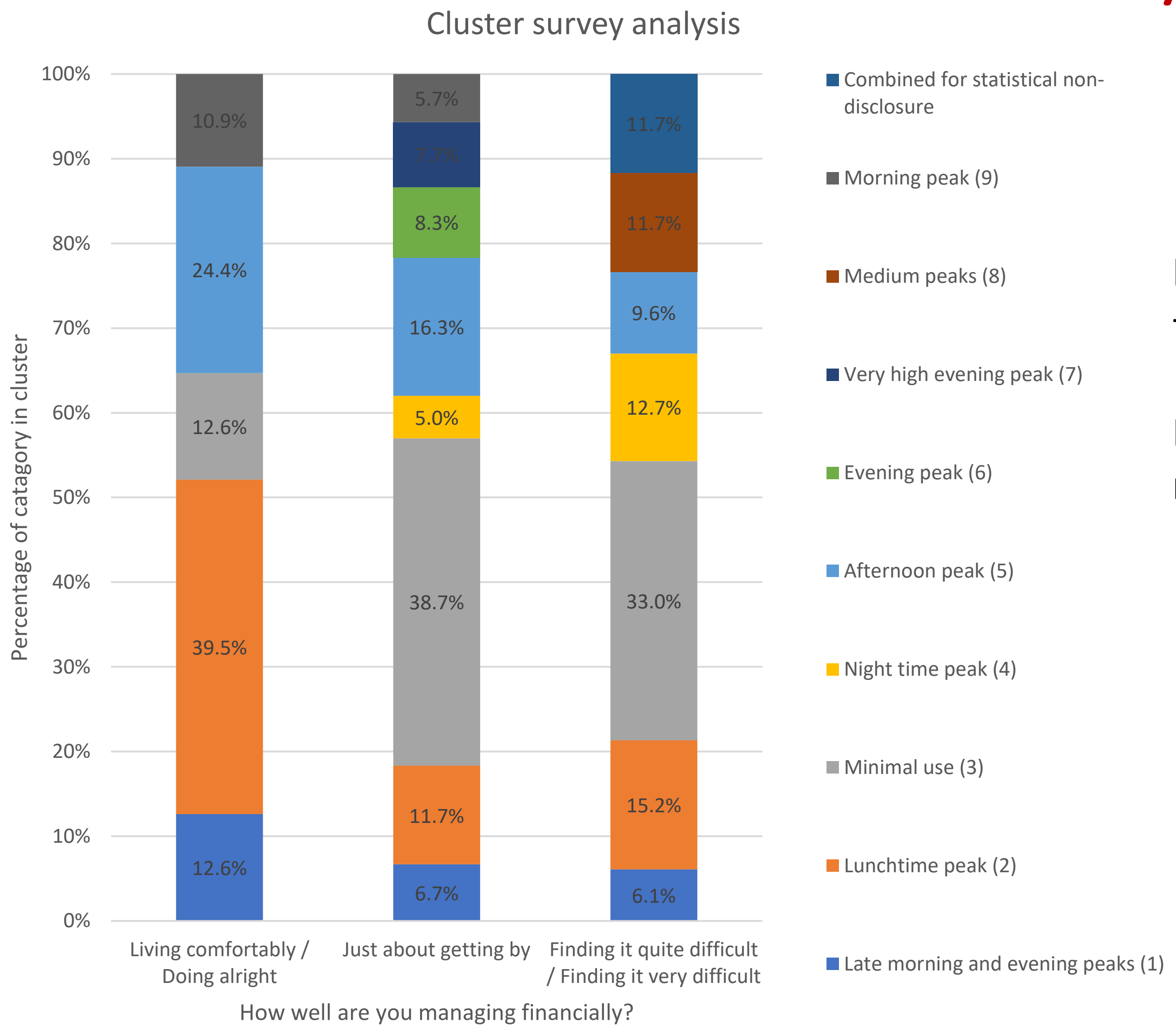
SHREWD Gas Cluster and survey results - clothes



Lunchtime peak is more common with tenants that say they **always** put more clothing on when they are cold

Minimal use is quite variable

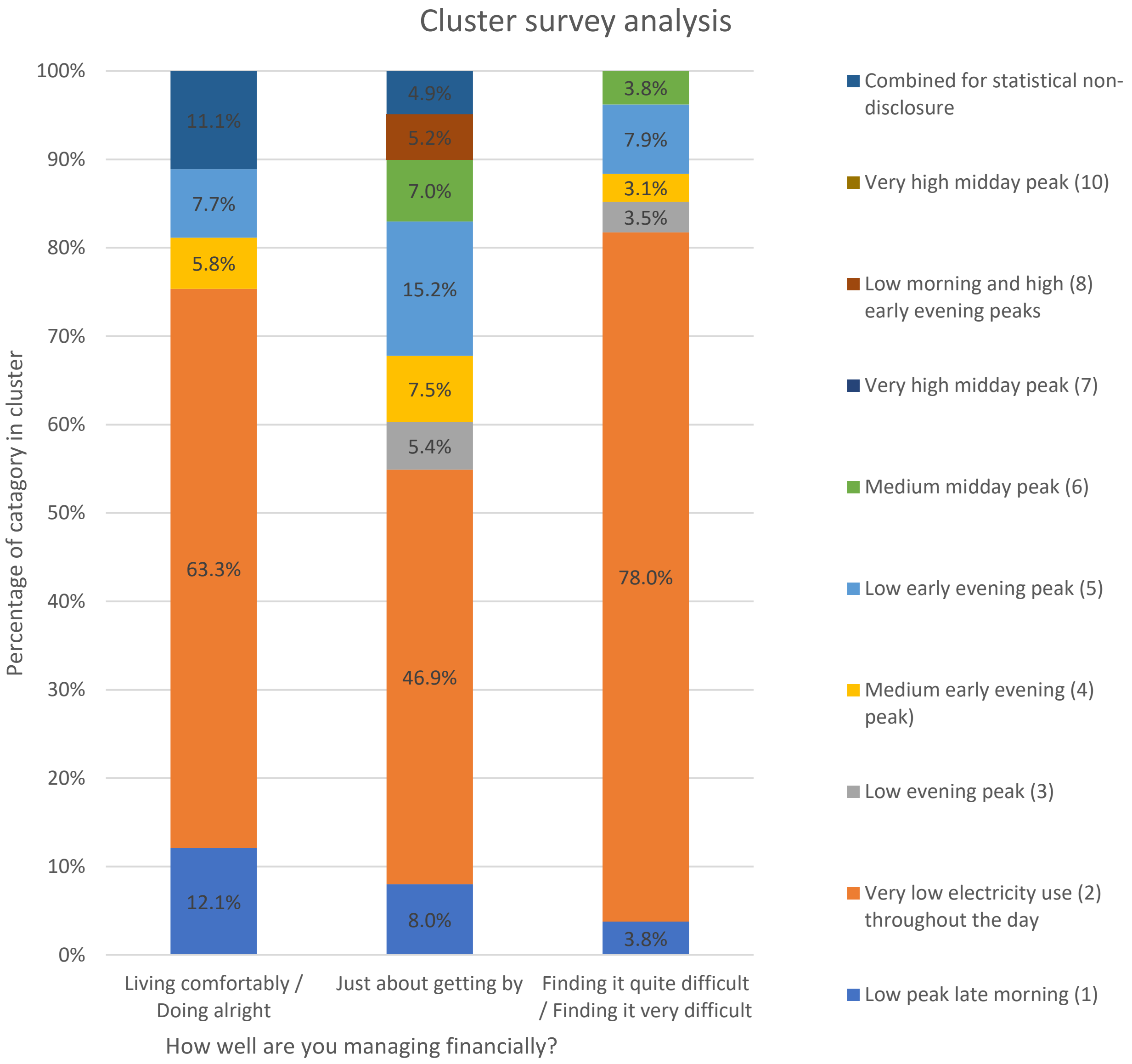
SHREWD Gas Cluster and survey results – managing financially



Lunchtime peak is more common with tenants that say they **are living comfortably/doing alright**

Minimal use is more common with tenants that say they **not "living comfortably/doing alright"**

SHREWD Electricity Cluster and survey results – managing financially



Very low electricity use throughout the day is the dominant, but **unpredictable**

SHREWD summary

- Social homes use less energy than the Welsh SERL data

- More energy behaviours than expected
- Electricity and gas clustering behaviours are different when combined with survey results
- Occupants use a mix of behaviours that can be different depending on their attitude to energy saving and the presence of damp.

- Smart meter data suffers from data loss, daily is good, half hourly needs to be used with care
- Smart meter great for stock level research, more care is need for individual homes

Social Housing Research on Energy from Welsh Data (SHREWD)

Smart Energy Research Lab project 2020 to 2023

Any Questions?

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SERL evaluation projects: highlights & reflections

SERL consortium final event
Eoghan McKenna
6th December 2023

SMART ENERGY RESEARCH LAB
UNIVERSITY RESEARCH FOR PUBLIC GOOD

Contents

- Brief summary of project, SERL's role and (selected) project highlights:
  - Smart Energy Savings (SENS) Competition
  - Green Homes Grant Voucher Scheme Evaluation
  - Domestic Energy Monitoring via SERL
- Some personal reflections of mine

Smart Energy Savings (SENS) Competition

- BEIS-commissioned project to evaluate innovative products and services that harnessed smart meter data to deliver additional energy savings in homes (Feb 2019 – March 2022)

Primary Research Question: *What is the added [gas and/ or electricity] saving achieved from the [SENS product], over and above the baseline smart meter customer proposition (i.e. a smart meter, an in-home display (IHD), and energy efficiency advice provided at install)?*

- SERL's role was to access smart meter consumption data for the trials, provide a single consistent source of treatment and control group data for independent evaluation of trials by Ipsos (with partners)

SENS highlights

- Design of statistically robust large-scale household trials to understand energy consumption impacts, along with a package of wider research (survey, qualitative insights and engagement data)
- Development of Data Governance Framework that enabled successful recruitment and supplier-independent smart meter data collection for 6,000+ trialists across 5 trials involving different Energy Suppliers and competition partners
- 2 SENS products demonstrated statistically significant gas consumption savings (in addition to 'baseline' smart offering): GEO 5%, GenGame 4.6%

Green Homes Grant Voucher Scheme Evaluation

- BEIS-commissioned project to evaluate the outcomes of the Green Homes Grant Voucher Scheme (Sept 2020 – June 2023) in terms of:
  - Satisfaction; energy use carbon and bill savings; health benefits; alleviating fuel poverty; quality of installations; employment and business growth; value for money
- SERL's role was to:
  - Assess the feasibility of using smart meter data for the evaluation, incl. confirmation of smart meter data consent processes
  - Recruit GHG participants and collect smart meter data and survey data
  - Assess the energy, carbon and bills savings of the GHGS Vouchers Scheme using this smart meter data

GHGVS highlights

- 2428 Vouchers applicants recruited, with smart meter data and survey data collected
- High recruitment rate (35.8%)
- Novel evaluation method for estimating energy use impacts using SERL Observatory as a matched control group
- Evaluation was able to identify robust evidence of participation in GHGVS generating energy, carbon, and bill savings, but savings varied by measure type
- Air source heat pumps and insulation measures generated clear savings in energy, carbon emissions and energy bills*
    - Air source heat pumps – Gas: reduction 26.8 kWh/day (95% saving), Electricity: increase 6.2 kWh/day (46.3% increase)
    - External solid wall insulation – 3.3 kWh/day (9.9% reduction)
    - Cavity wall insulation – 1.9 kWh/day (5.8% reduction)
    - Loft insulation – 1.4 kWh/day (4.2% reduction)
    - Pitched roof insulation – 1.3 kWh/day (4.7% reduction)
- Solar thermal systems achieved no savings

* In previously gas centrally heated properties

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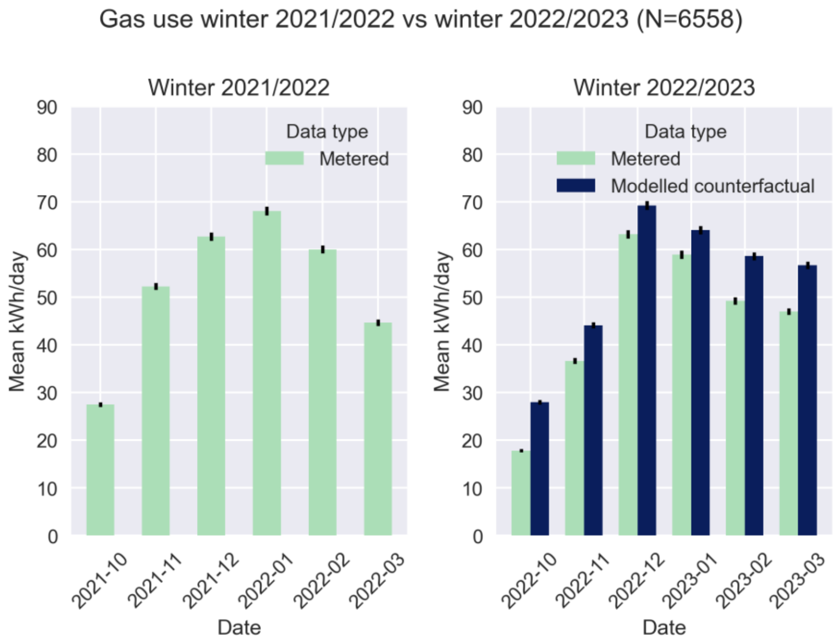
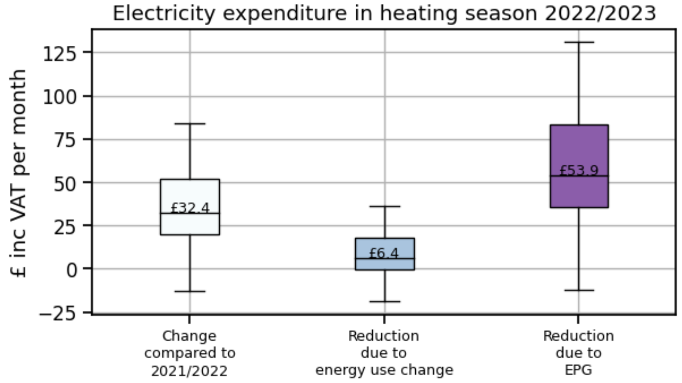
Domestic Energy Monitoring via SERL

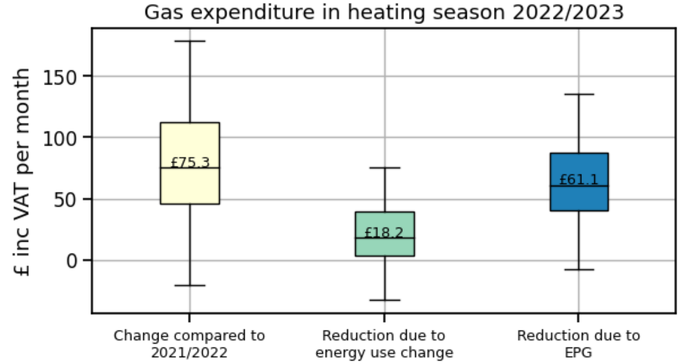
- DESNZ-commissioned project to provide data and insights on household energy consumption over the winter of 2022/2023, and evidence to support evaluation and development of energy policies. April 2023 – March 2024.
- SERL's role:
  - to provide analysis and insights to DESNZ relating to the SERL Observatory dataset
  - to provide aggregated and anonymised data based on the SERL Observatory to DESNZ on a regular monthly basis

DEMS highlights

- Average reduction in domestic energy use in winter 22/23 (temperature adjusted) was:
  - **Gas: -7.96 kWh/day (-14.90%)**
  - **Electricity: -0.88 kWh/day (-9.09%)**
- Average increase in energy bills (temperature adjusted):
  - **+127% for gas expenditure to £150.7/month**
  - **+60.5% for electricity expenditure to £111.4/month**
- Price elasticity (temperature adjusted):
  - ***-7.6% for gas***
  - ***-12.7% for electricity***
- Average saving on household energy bills due to Energy Price Guarantee was £690 over winter 22/23 (£1090 including EBSS)







Reflections

- Demonstrated value of smart meter data for informing net zero energy policy
- Growth in smart meter-based monitoring and evaluation projects
- Significant evidence gaps remain (e.g. solar PV, solar thermal, etc.)
- Need for 'tried and tested' methods: opportunities to learn from field of epidemiology
- Value of large, representative, longitudinal, and contextually-rich 'Observatory' data

What’s next for SERL – EDOL and SERL Supplement funding

Funded via EDOL grant (until Dec 2027)

- Data collection and maintenance of the SERL Observatory panel
    - as need to collect SERL data for EDOL anyway

Funded via SERL Supplement (until July 2024)

- Provisioning of controlled SERL Observatory data
    - 24 active projects and new projects coming onboard
- Publishing SERL stats reports/datasets (Volumes 2 and 3)
- SERL must become self-funding by July 2024
    - Charging model: Data access fee for research projects using SERL data
    - Extending/broadening the user base

What's next for SERL – Beyond existing funding

- Long-term vision to develop SERL into national research facility
- Enhancements
  - Linking to new data – e.g. Understanding Society (Innovation Panel in 2024)
- Explore new avenues for funding
  - UK Smart Data for Research (ESRC) – call for data services / products
- Explore potential collaborations
  - ONS
  - Energy Systems Catapult
  - Smart Homes Lab and Energy House (Salford)

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Building on SERL – the Energy Demand Observatory and Laboratory

Tadj Oreszczyn

Professor of Energy and Environment

UCL Energy Institute

EDOL Intro slide

Partners

- University College London
  - Energy Institute
  - Advanced Research Computing (ARC)
- University of Oxford
  - Environmental Change Institute (ECI)
  - Department of Engineering Science

Funder

- Engineering and Physical Sciences Research Council (EPSRC) EP/X00967X/1
- Jan 2023 – Dec 2027

Vision: *transform residential energy use with data driven solutions, policies, and innovation to help meet UK net-zero ambitions.*

Goal:

make available a unique disaggregated, consistent, flexible, longitudinal resource of UK domestic energy data.

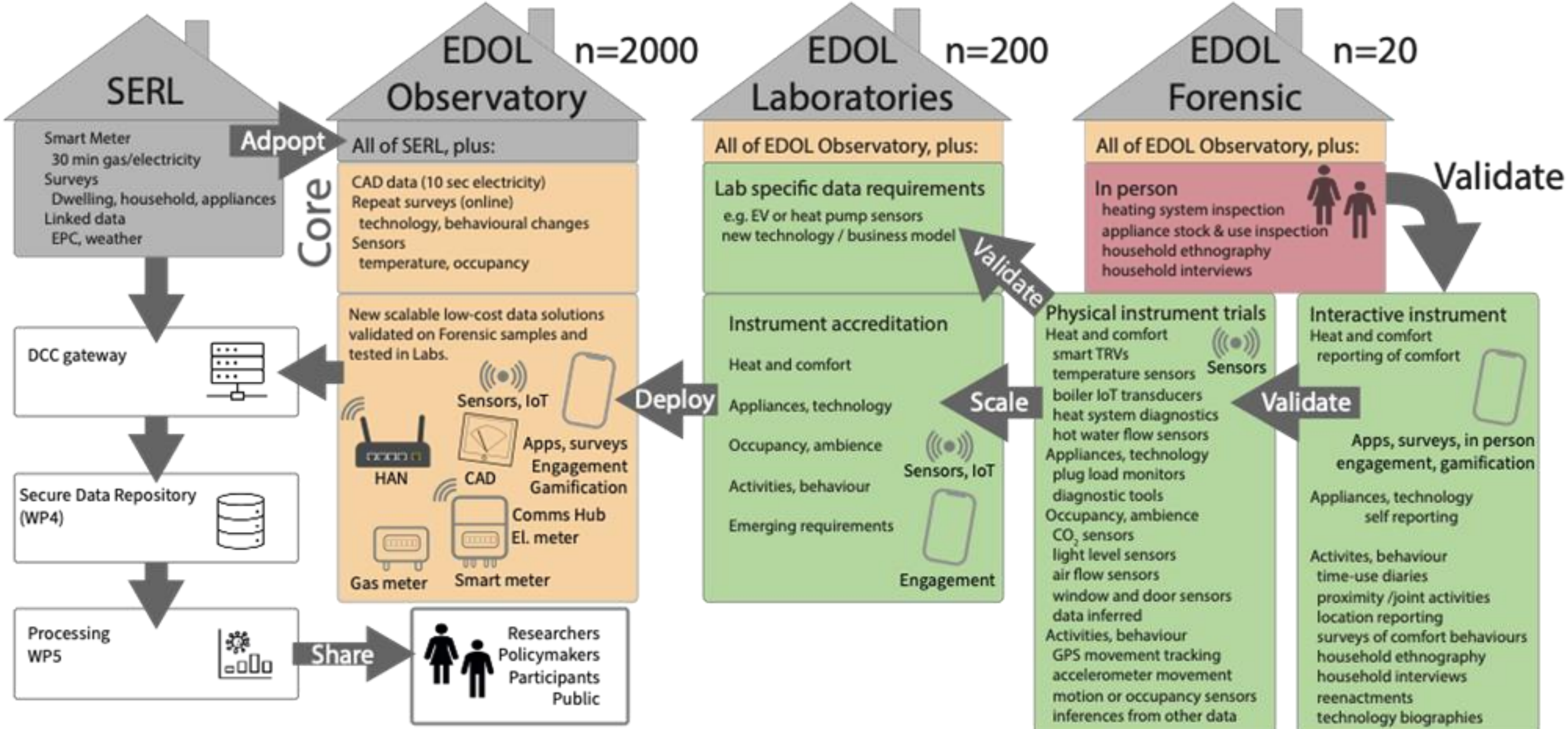
Aims and objectives?

1. to enable and strengthen foundational scientific understanding of how and why energy is used in homes through data-rich sociotechnical research.
2. to deliver applied research and modelling flexibly and responsively to a fast-moving technological and policy landscape.
3. to make representative and reliable data available to scientists, industry and policymakers.
4. to sustain the UK's world-leading research in data-driven approaches to energy data collection, analysis and access.
5. to innovate new, cost-effective, smart data solutions for collecting energy data at scale.

EDOL novelty: The **why** of energy use

1. **High resolution data (technical and social)**
   - SERL provides whole-home energy data
   - EDOL will collect many additional in-home data streams:
     - Temperature, smart thermostats/appliances, heat pumps, EVs etc.
2. **Disaggregation** of energy use to activities and appliances
3. **Longitudinally** over multi-year timescales
4. **Sufficient scale** for robust statistical analysis, use as a counterfactual etc.

Beyond SERL > EDOL



EDOL adapts SERL data collection methods and tests, validates and deploys novel social and physical monitoring instruments

EDOL Challenges

Reducing energy waste

Quantifying wasted energy, assess potential to reduce waste & identify tech. & behavioural solutions

- Improved design & co-design of control systems, technologies, services, information and advice
- Policy and intervention strategies to ensure wellbeing while reducing energy demand
- Papers on: definition of wasted/unused energy, occupancy & its impact on domestic energy use
- Algorithms for predicting occupancy

Managing Energy Disruptions

Disruptions = significant changes in life

- **Internal:** Job change, moving home, life events
- **External:** Pandemics, extreme weather, policy changes
- **Key Question:** Effects of disruptions on household energy use, bills, and CO_2 emissions?
- **Impact:** Affects decision-making for individuals, government, etc.

EDOL Challenges

Flexible demand for flexible systems

Supply systems: less short-term (inertia) and less long-term (seasonal) storage

New (smarter?) electrical loads, e.g. EVs, heat pump, PV and batteries: more (peak!) demand / more flexible resources / more agency? (AI, DSOs, Prosumers)

- *How do emerging **technologies** and **behaviours** shape load profiles?*
- *What is the potential for **interventions** to (re-)shape load profiles?*
- *How to **measure** and **attribute** the success of interventions?*

Energy demand modelling

- A **comprehensive longitudinal dataset is needed** to test validity of models, develop better algorithms for specific energy use, ground models in occupant behaviour, or train empirical models.
- Models need continuous grounding in high quality disaggregated energy data to account for future changes in behaviour, climate, energy costs, and tech.
- How do AI models perform relative to existing stat & engineering models of disaggregated demand?
- What are strengths & weaknesses of competing models in helping net-zero transition?

Thank you

- **EPSRC- Our funder and partner**: All work to develop the Smart Energy Research Lab is supported by an Engineering and Physical Sciences Research Council grant - EP/P032761/1.
- **30 Consortium members** (co-investigators, researchers, and technical staff) of the SERL Consortium across 8 organisations who have contributed to the development of SERL.
- **Our SERL participants**, Over 20,000 homes have consented to provided data either to the Observatory of Labs and completed questionnaires.
- **Funders and partners of additional SERL Labs and use cases**: including DESNZ, DHLUC, Ipsos MORI, Frontier Economics, Western Power Distribution.
- **Our Advisory Board** – who have remained fully engaged and supportive.
- **Our data Governance Board** - unsung hero's
- **Our Research Programme Board** – who played a key role in setting up the consortium projects.
- **Public Interest Advisory Groups**

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Join us for Drinks

More information

We welcome research project applications who want to utilise SERL data

- **Information on the process: https://serl.ac.uk/researchers/**
- **SERL Observatory dataset** (UKDS SN8666):
  - https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8666
- **SERL Stats Report and Data** – available via https://serl.ac.uk/key-documents/reports/
- **SERL projects:** https://serl.ac.uk/projects/
- **SERL Research Publications**: https://serl.ac.uk/key-documents/

SERL Contact Details:

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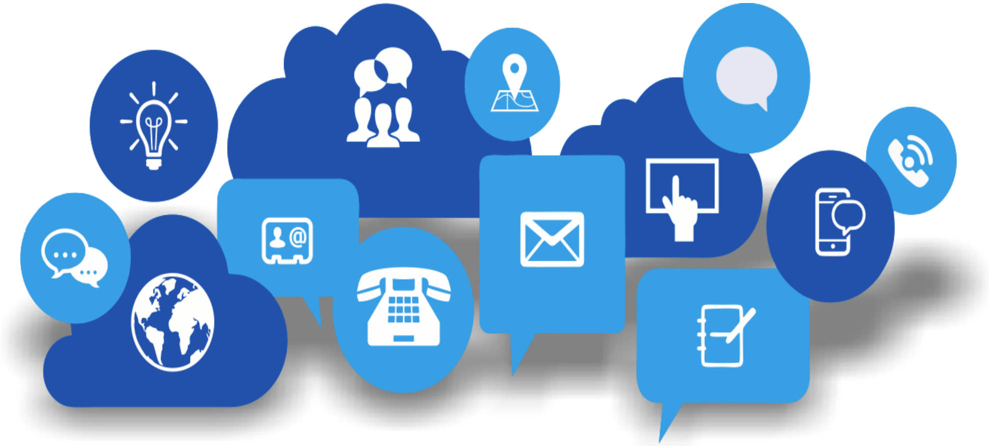
EDOL: https://edol.uk/



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