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
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
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)

Location data
- Region, LSOA, IMD quintile
- All participants

Energy Performance Certificate (EPC)
- ~50% of participants
- Sourced from EPC Register

Weather data
- ECMWF ERA5 data
- Hourly longitudinal data
- 30km resolution
- 24 variables

SERL Observatory dataset
- 13k GB households
- 2018-ongoing

SERL Survey
- Initial sign-up survey (2019-2021): 40 questions on the dwelling and household
- 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/](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 R^2 calculated using cross-validation testing errors)

• Roughly *twice the power of other studies/datasets*
  • which report adjusted R^2 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)
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, SHREWDM
• 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).
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
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.


- Private Eye magazine references to SERL EPC work (Jun, Aug 22).

- ‘Smart Energy, smart buildings, smart health’ (Aug 21) COP26 UCL ‘explainer’
SERL EPC Paper - EPCs overpredict energy use in C to G properties, and over predict the change between bands
Impact of increasing energy costs in UK in 2022/23 – Behavioural response – Space Heating

- 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/](https://osf.io/preprints/socarxiv/984yh/)
SERL Research outputs
Impact of increasing energy costs in UK in 2022/23 – Energy consumption by household type

**Electric**

- All Households
- Over 75
- Young child
- Ill or Disabled
- Financially Struggling
- Just about getting by
- PPM
- Social housing
- Always WfH
- Electric central heating

**Gas**

- All Households
- Over 75
- Young child
- Ill or Disabled
- Financially Struggling
- Just about getting by
- PPM
- Social housing
- Always WfH
- Electric central heating
SERL Research outputs

Actions that saved fuel bills (£/month during heating season)

- Turn appliance off standby when not in use
- Avoid cooker for main meal
- Dry clothes with a tumble dryer
- Reduce boiler flow temperature
- Heat fewer spaces
- Turn down radiators in heated rooms
- Heat fewer hours
- Reduce thermostat by 1°C

£0.00 £1.00 £2.00 £3.00 £4.00 £5.00 £6.00
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
Impact highlights (academic papers 1)


Impact highlights (academic papers 2)


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
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.

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DOR methodology – a primer

As per 2019 method statement\textsuperscript{1}:

• For a given dwelling, DOR uses monitored energy demand & weather data to calculate annual totals for:
  • Energy demand (kWh/m\textsuperscript{2})
  • Greenhouse gas (GHG) emissions (kgCO\textsubscript{2}e/m\textsuperscript{2})
  • Energy cost (GBP/m\textsuperscript{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.

\textsuperscript{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.

---

DOR – application to SERL dataset

• Refined DOR algorithm coded in Python, applied to all dwellings in the SERL dataset with data available for at least one full year (some 4400 dwellings).

• Applied to rolling year-long windows:

\[ \text{DOR calculation window} \]

\[ \text{Annual DOR score running year ending on date} \]

\[ \text{Daily energy demand (kWh)} \]

\[ \begin{align*}
\text{Energy demand score} & \quad \text{DOR}_{\text{ED}} = 100 \times \frac{\text{Weather-corrected annual energy demand}}{\text{Benchmark annual energy demand}} \\
\text{GHG emissions score} & \quad \text{DOR}_{\text{GG}} = 100 \times \frac{\text{Associated annual GHG emissions}}{\text{Benchmark annual GHG emissions}} \\
\text{Energy cost score} & \quad \text{DOR}_{\text{EC}} = 100 \times \frac{\text{Associated annual energy cost}}{\text{Benchmark annual energy cost}}
\end{align*} \]

(Image produced from analysis of non-SERL data)


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

- 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).

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

- 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.

Explanatory power of combined LASSO regression models

<table>
<thead>
<tr>
<th>Independent variable set</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building variables</td>
<td>0%</td>
</tr>
<tr>
<td>+ occupant behaviour</td>
<td>10%</td>
</tr>
<tr>
<td>+ household characteristics</td>
<td>20%</td>
</tr>
<tr>
<td>+ appliances</td>
<td>30%</td>
</tr>
</tbody>
</table>

Building variables

35%

35%
Findings: Factors influencing UK domestic energy demand

Explanatory power of combined LASSO regression models for DOR-measured energy demand

Explanatory power of combined LASSO regression models for SAP-predicted energy demand

Adjusted R²

<table>
<thead>
<tr>
<th>Independent variable set</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building variables</td>
<td>35%</td>
</tr>
<tr>
<td>Building variables + occupant behaviour</td>
<td>40%</td>
</tr>
<tr>
<td>Building variables + occupant behaviour + household characteristics</td>
<td>45%</td>
</tr>
<tr>
<td>Building variables + occupant behaviour + household characteristics + appliances</td>
<td>46%</td>
</tr>
</tbody>
</table>

Adjusted R²

<table>
<thead>
<tr>
<th>Independent variable set</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building variables</td>
<td>53%</td>
</tr>
</tbody>
</table>
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:

<table>
<thead>
<tr>
<th>Variable set</th>
<th>Number of significant predictors in final combined model for DOR-measured energy demand</th>
<th>Number of significant predictors in final combined model for SAP-predicted energy demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building variables</td>
<td>19</td>
<td>24</td>
</tr>
<tr>
<td>Occupant behaviour</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Household characteristics</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Appliances</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

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

References


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.

Source: Bennett (2020)
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.

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

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.
Results

HUT distribution

Typical HUT is ~ 80 minutes
Results

Gas use vs outdoor temperature

Gas use during heat-up

Outside temperature

Strong negative correlation

No significant correlation with other weather variables.
Results

HUT vs EPC score

Weak but significant correlation

EPC score
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.
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
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.

Our analysis attempts to overcome the above challenges
SERL Observatory dataset
13k GB households
2018-ongoing

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)

Location data
- Region, LSOA, IMD quintile
  - All participants

Energy Performance Certificate (EPC)
- ~50% of participants
  - Sourced from EPC Register

Weather data
- ECMWF ERA5 data
  - Hourly longitudinal data
  - 30km resolution
  - 24 variables

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

UKDS study number 8666
Data descriptor paper: Webborn et al. (2021)
Statistical report: Few et al. (2022)
EPCs overpredict energy use in C to G properties, and over predict the change between bands.
• 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
New homes rated via full SAP show good agreement
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.

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

Autocorrelation function
All days of the week

Correlation coefficient

SERL observatory daily electricity consumption data: edition04
Subsample of 15 households
'Habituality' (1)

Autocorrelation

SERL observatory daily electricity consumption data: edition 04
Subsample of 15 households
'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

Date (2021)

SERL observatory daily electricity consumption data: edition04
Subsample of 15 households
'Habituality' (2)

Seasonal Trend Decomposition

Raw elec demand:

Trend

+ Seasonal (weekly)

+ Residuals

Small residuals = high habituality

Large residuals = low habituality

Date (2021)

SERL observatory daily electricity consumption data: edition04
Subsample of 15 households
Modelling

Predictors:

- Household characteristics
- Appliance ownership

Data:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto-correlation</td>
<td>Daily total</td>
<td>Daily total</td>
</tr>
<tr>
<td></td>
<td>a.m. peak</td>
<td>a.m. peak</td>
</tr>
<tr>
<td></td>
<td>p.m. peak</td>
<td>p.m. peak</td>
</tr>
<tr>
<td>Decomposition</td>
<td>Daily total</td>
<td>Daily total</td>
</tr>
<tr>
<td></td>
<td>a.m. peak</td>
<td>a.m. peak</td>
</tr>
<tr>
<td></td>
<td>p.m. peak</td>
<td>p.m. peak</td>
</tr>
</tbody>
</table>
Preliminary results *

Predictors:

- Household characteristics
- Appliance ownership

![Venn diagram showing predictors and their relationships with autocorrelation and decomposition]

- Autocorrelation:
  - Dishwasher (-)
  - Tumble-dryer (-)
  - Washer-dryer (-)
  - Age >65 (+)
  - Shower (-)

- Decomposition:
  - 2-person (-)
  - Children (+)
  - Age all >65 (+)
Next steps

SERL:
• Refinement of metrics/models
• Journal paper in preparation

Future:
• Re-analysis of flexibility trial data
• Covid as a natural experiment
Thanks for listening!

Contact:

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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
Scope of presentation

• Starting point and aims
• Methodology
• Selected results
Starting point and aims

• Averages demand profiles...

... vary between groups

• 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

Weekly rhythms

Start of Covid-19 lockdown 1

Christmas Day
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
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.

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)

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](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

![Graph showing energy use and demand profiles](image-url)
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)

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
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

Average daily electricity consumption

Average daily gas consumption
SHREWD vs Welsh SERL energy results

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

<table>
<thead>
<tr>
<th></th>
<th>SHREWD</th>
<th>Welsh SERL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Electricity Consumption (kWh)</td>
<td>Mean: 6.78, SD: 4.35</td>
<td>Mean: 9.47, SD: 7.93</td>
</tr>
<tr>
<td>Daily Gas Consumption (kWh)</td>
<td>Mean: 17.92, SD: 19.86</td>
<td>Mean: 33.8, SD: 34.1</td>
</tr>
</tbody>
</table>
• 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

Cardiff average monthly air temperature

Air temperature Deg C

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

Nov-21, gas, all cluster (n=713)

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

Can you keep comfortably warm during cold weather?

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
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

Cluster survey analysis

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

**Minimal use** is quite variable
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

Cluster survey analysis

How well are you managing financially?

- Living comfortably / Doing alright
- Just about getting by
- Finding it quite difficult
- Finding it very difficult

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?
SERL evaluation projects: highlights & reflections

SERL consortium final event
Eoghan McKenna
6th December 2023
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
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)
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.
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 CO2 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**

**Join us for Drinks**
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/
SMART ENERGY RESEARCH LAB
UNIVERSITY RESEARCH FOR PUBLIC GOOD