UK Government

EPC Accuracy Research Project

Part 1: Gas Heated homes

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Part 2: Electric heated homes

Department for Energy Security and Net Zero (2025)

Acknowledgements

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Executive summary

This report investigates why the estimation of energy demand by the method underlying Energy Performance Certificates (EPCs) differs from actual household energy use. EPCs are central to UK energy policy and consumer decisions, yet they were designed as comparative ratings rather than precise consumption forecasts. Using smart meter data from over 1,100 homes, temperature monitoring, and forensic surveys, the study quantifies the performance gap and explores its causes for both gas-heated and electrically-heated homes.

For gas-heated homes, EPCs currently overestimate energy use by an average of 16.0%. When models are updated to reflect the latest RdSAP (Reduced input SAP, Standard Assessment Procedure) version, actual weather, post-EPC upgrades, and real occupancy patterns, the gap narrows to 10.9%. More than half of this improvement is due to energy efficiency measures installed after the EPC was issued, highlighting the need for dynamic updates. Electrically-heated homes show a larger discrepancy: they consume about 31% less energy than predicted, with the gap widening to nearly 47% in December. These homes often occupy EPC bands F and G because ratings are cost-based and electricity is significantly more expensive than gas, despite lower actual energy use. Several factors drive these inaccuracies:

1. Model assumptions:
    a. Overprediction of space heating energy requirements in gas-heated homes, particularly in older and less insulated buildings suggesting these may be pessimistically modelled at present.
    b. Overprediction of year-round electricity use and underprediction of summer gas use in gas heated homes.
    c. Internal temperatures: gas heated homes are warmer than SAP assumes, while electrically heated homes appear slightly cooler than SAP assumes.
    d. Living area/non-living area (SAP 2 zone model assumption) temperature difference is substantially overstated in SAP for gas heated homes, and slightly for electrically heated homes.
    e. Ventilation: There is less ventilation/air exchange in some homes (measured in field trials) than SAP default minimum infiltration rates (0.5 air changes per hour) inflating heating demand from high ventilation rates.
    f. Solar gains underestimated by up to 54% in sunny winter months.
2. Process issues:
    a. Post-EPC upgrades (e.g., boiler replacements) account for >50% of gap reduction in gas heated homes when model updated.
    a. Outdated EPCs and RdSAP default values which have been subsequently updated alongside assessor errors (average impact 6%, higher for misclassified dimensions/heating systems).
3. Electrically heated homes: Complexity of tariffs and heating patterns; SAP overestimates internal temperatures and fails to capture zoned heating behaviour.

The findings suggest that improvements could be made through: a) linking EPCs to energy efficiency administrative datasets such as NEED to enable automatic updates when regulated improvements occur, b) revising assumptions on ventilation and fabric heat loss, solar gains, hot water, and appliance electricity use, and c) improving assessor training and access to full SAP input data. Future work should continue to validate the EPC calculation methodology (currently transitioning from SAP to HEM (Home Energy Model)) against empirical data and recruit targeted samples for ongoing calibration.

Extended summary

This report is the outcome of the Energy Performance Certificate (EPC) Accuracy project (Ref BE24022) funded by the Department for Energy Security and Net Zero (DESNZ). The aim of the report is to help understand why the EPC modelled energy use differs from metered energy use to support the EPC Action Plan and the development of the Home Energy Model (HEM). This report provides new empirical evidence that builds on literature that has identified weaknesses in the historic EPC process and Standard Assessment Procedure (SAP) calculation which in turn provides insight into elements to be considered in the Home Energy Model (HEM) development. The report is split into two parts, the first covers analysis of gas heated homes while the second part focusses on electrically heated homes.

This research on gas heated homes uses new evidence of energy use and temperatures from 1,136 homes (from the Smart Energy Research Lab, SERL; and the Energy Follow-up Survey, EFUS) to explore shortcomings with EPCs and RdSAP. On average, homes are found to be warmer and use less energy than assumed in RdSAP. The average performance gap between EPC-modelled and actual energy use intensity emerges as 16.0%, and this reduces to 10.9% after adapting the EPC calculation by: updating to RdSAP version 9.94, using the actual weather in the calculation, updating to include post-EPC energy-efficiency improvements, and updating to reflect actual occupancy and thermostat set points. More than half of the improvement is associated with energy efficiency upgrades installed after the EPC was generated.

The analysis of gas heated homes focuses on comparing monitored with modelled energy and internal temperature data for two main samples of homes: 674 gas-heated, smart-metered SERL Observatory homes; and 462 gas heated Energy Follow-up-Survey (EFUS) homes with monitored internal temperature data. This is supported by temperature data gathered from 200 homes as part of the GHG-SMETER project. The analysis in this report is unique compared to previous EPC research in that it compares not only total annual energy use, but energy use disaggregated by fuel and by season. It also compares the EPC modelled energy use for the lodged EPC (Model 0), corrects all EPCs to the latest RdSAP 9.94 (Model 1), for weather (Model 2), post-EPC energy improvements (Model 3) and actual occupancy (Model 4) by building a RdSAP 2012 model of each monitored home using EPC input data, NEED energy efficiency intervention data, and SERL occupant data. These model scenarios were selected to address some of the common reasons suggested for the discrepancy between metered and EPC modelled energy use. Additionally, for a sub-sample of 41 homes it corrects for EPC assessor error and changes to the home since the original survey by visiting homes to undertake a full SAP assessment.

Key findings from the analysis of gas heated homes include:

1.

The difference between measured and modelled energy use is often attributed to underheating of poorly insulated properties. Analysis of EFUS data shows that less efficient homes (EPC band G) are 2.5°C colder than efficient homes (band A&B), on average. It is often wrongly assumed that SAP assumes a fixed internal temperature, whereas in fact SAP calculates a reduction in mean internal temperature for less efficient homes. On average homes are measured to be warmer than SAP calculates and therefore underheating cannot explain the full extent of the difference between modelled and measured energy use.

2.

The average gap between EPC modelled and metered delivered energy use in 2021 is 16.0%. However, when the SAP calculations are modified to account for the latest version of RdSAP (9.94), the weather during monitoring, actual occupancy and modifications to the home after the EPC was undertaken, the gap reduces to 10.9%. Over half of the reduction in performance gap is attributed to changes to the building efficiency that have been made between the EPC assessor survey and the date of metering energy use, on average. This supports the proposal to update EPCs whenever there is a significant change to the building's efficiency. This research has demonstrated that it is feasible to automatically update existing EPCs using a version of the National Building Model[1] (NBM) with EPC input data held by MHCLG and with energy improvement data held by DESNZ (installations of energy efficiency measures supplied by Ofgem, and installation of new boilers supplied by Gas Safe Register, both of these are currently collated as part of the National Energy Efficiency Data-Framework – NEED), subject to appropriate permission for this data linking. This would improve EPC accuracy and could be done automatically when a regulated change to a building is undertaken.

3.

Reasonable agreement (+/-10%) between average total RdSAP modelled and metered outcomes do not validate the assumptions used in RdSAP. This is because erroneous assumptions can cancel each other out when examining an average property, or the annual energy use. Our analysis demonstrates several cases where this happens. For example, there is little difference between metered and modelled total summer energy use, but metered summer electricity use is consistently less than modelled, while metered summer gas use is more than modelled. Also, new home EPCs underestimate energy use whereas the reverse happens in older properties.

4.

The following differences between measured data and RdSAP modelled data have been identified which indicate areas of potential SAP/RdSAP improvements:

a. Mean Internal Temperature (MIT) – The measured MIT is higher than modelled in SAP, including for less efficient homes (F&G). If the measured MIT were used in the SAP calculation this would tend to increase the modelled energy use thereby

[1] The National Building Model is a DESNZ model that includes a SAP calculation that can be applied to a stock of buildings.

making the performance gap larger. While the Zone 1 (living area with modelled higher occupancy and higher temperature setpoint) measured and modelled temperatures are reasonably similar, Zone 2 (rest of the dwelling with assumed lower occupancy with lower setpoint temperature) temperatures are different. SAP assumes that Zone 2 is cooler than Zone 1 by up to 3°C, although the exact difference depends on the controls and the heat loss parameter. Measured data shows little difference in temperature between Zone 1 and 2 and so does not support the two-zone heating model in SAP. Homes with more advanced heating controls tend to have higher MIT, while they are calculated to have lower MIT in SAP. Several hypothesises could explain this gap, e.g. the benefit of increased control could be taken as increased comfort, or homes with better controls are more affluent. Measured data also shows very little difference between weekend and weekday heating schedules.

b. Summer gas use is 34% greater than RdSAP modelled (as per the lodged EPC - Model 0), and this gap increases for less efficient homes. RdSAP assumes a relatively constant gas use across the summer months derived from hot water and cooking i.e. not significantly changing with external temperature, whereas metered data shows an increased energy use in the colder summer months suggesting that space heating may be used during this time. This is consistent with summer monitored data from gas boilers.

c. Electricity use in gas heated homes is 18.2% lower than modelled by RdSAP. The modelled electricity use shows slightly greater seasonal dependence than is observed in the metered electricity use, with the discrepancy increasing up to 20.8% in December. This impacts the SAP Energy Efficiency Rating, which is based on fuel cost, because the standard electricity tariff is almost 4 times more expensive than gas. Since most winter electricity uses result in incidental heat gains, modelled electricity use reduces the calculated gas use for space heating.

d. RdSAP appears to correctly predict the total delivered energy (gas and electricity) in summer months at approximately 69 kWh/year per m² of floor area, however it over-predicts the electricity use and under-predicts the gas use. The impact of this is that for a delivered energy metric the summer performance gap is small but for a primary-energy or fuel-cost metric the summer gap will appear large.

e. Heat Loss: The performance gap for heat loss is largest in homes with poorly insulated walls, roofs and floors, and in older homes, which have lower heat loss than modelled. This gap reverses in new homes which have higher heat loss than modelled. This gap reversal is consistent with analysis undertaken on other empirical data including NEED, co-heating data, and field data such as the micro-CHP trials. This suggests that older homes are better insulated than RdSAP assumes, and modern homes may be less insulated than assumed. There are theoretical (e.g. thermal bypass) and motivational reasons (e.g. new build assessors meeting building regulations, default assumptions for existing buildings) that this may be happening.

f. Ventilation rates are one of the most difficult aspects to model, yet critical to accurately predicting space heating. RdSAP-2012 assumes an average heating season air change rate (air changes per hour) of 1.02 ach for F&G rated homes compared to 0.69 ach for A&B-rated. Empirical measurements suggest ventilation rates are often lower than modelled both for new and existing homes. For naturally ventilated buildings RdSAP's minimum air change rate is 0.5 ach (for IAQ reasons), however ventilation rates in real homes can be lower than this, so some homes will be modelled as using more energy than they do in practice. Minimum assumed ventilation rates should be reviewed in conjunction with minimum requirements for air quality.

g. April 2021 was the sunniest April on record; this provided a natural experiment to observe the impact of passive solar heating because this occurred during a cold month. RdSAP appeared to underpredict, by 54%, the impact of solar heating compared to actual monitored data. This may be because RdSAP-V9 uses algorithms to predict the glazing area based on the property age. RdSAP-10 requires glazing areas to be measured rather than modelled which may improve the modelled performance. However, the usefulness of incidental solar gains are not only impacted by glazing area but other factors such as orientation and thermal mass, which may also contribute to the observed gap. Further research into the effect of weather variables beyond external temperature, including solar irradiance and wind conditions, would be useful.

h. Combi boilers and space heating system efficiency: many homes where the lodged EPC records old inefficient boilers (less than 70% efficient) have had their boilers replaced after their EPC Assessment, with this information lodged in NEED. For such cases, the model was regenerated using the PCDB notional dwelling boiler (as detailed information about the boiler specifications were not available), and this significantly reduces the performance gap for those homes. The performance gap decreased from an average of -22.1% (model scenario 0) to -9.5% (model scenario 4) for homes which had a boiler replacement, compared to an improvement from -13.6% to -12.5% on average for all other homes. However, analysis of the summer gas use suggests that the benefit of a combi boiler for hot water efficiency is overestimated in RdSAP, as the metered summer gas use is higher than modelled for system boilers and the gap increases for combi boilers.

5.

The above inaccuracies in SAP/RdSAP combine in a complex way. It would, however, be possible to produce a version of SAP calibrated using SERL and EFUS data, potentially using SMETER methods, to improve the algorithms and assumptions. This calibrated model, combined with real occupancy data, could be used to produce a significantly more reliable model of energy use for a homeowner, to assess the impact of refurbishment measures and running costs. The principle can also be applied with HEM as it supplants SAP. However, even such a model could not overcome EPC assessor error.

6.

Assessor error results in a 6% change in average predicted annual space and hot water heating. In some cases the impact can be larger – predominately where the building dimensions, heating system or wall insulation are wrongly classified. Assessors should be trained to better assess these critical parameters and be supported with historic EPC data, height data (Lidar), and energy efficiency records, such as those collated by NEED (energy efficiency retrofit and boiler improvements) to avoid errors.

7.

Undertaking a full SAP on an existing house by an expert assessor reduces the performance gap compared to an RdSAP assessment by a conventional assessor. However, the majority of this improvement is associated with new measures installed and assessor error rather than the difference in conventions between SAP and RdSAP. In contrast, newly built homes that have a full SAP assessment using construction data receive a worse EPC when subsequently assessed for sale using RdSAP. EPC accuracy would be improved for buildings constructed after 2008, when it became compulsory to have an EPC as built, if RdSAP assessors were allowed access to the full SAP calculations used for building control.

Research shows that improvements to EPC accuracy could be seen in from gas heated homes in the following areas:

EPC Data and Processes

a. Primary energy should not be the main energy metric displayed on an EPC certificate as it is not directly comparable to metered data, and in gas heated homes it distorts the significance of non-space heating energy use.
b. All possible steps should be taken to ensure EPCs are carried out which reflect the current state of buildings in the stock (i.e. reduce the degree to which the EPC register data is out of step with reality). Buildings are being continually improved as a result of incentives and grants for insulating homes or changing heating systems, and because of regulations requiring that technologies on the market meet certain energy efficiency standards, for example boilers, windows, lights and appliances.
c. If energy efficiency installation data, such as that collated by NEED, were used to support better EPCs then it would be useful if the required data were collated in a format that can be easily integrated with EPCs, e.g. exact boiler replacement type and regulated window replacement.
d. The best available data should be used by an assessor when undertaking an EPC assessment. If a full SAP/HEM has been undertaken for a property this data should be used as the starting point for an assessor undertaking an update/renewal EPC calculation.

e. EPC Registry data would be more useful if it included more complete PV data and how the transaction type 'new dwelling' was classified in relation to change of use. At present, the public data reports the percentage of the roof covered by PV panels, but Domestic Energy Assessors (DEAs) can choose whether to report this or instead report the kW peak. As a result the public EPC data does not accurately reflect PV deployment. With regards to the 'new dwelling' certificates, DEAs are required to manually check if there is an existing EPC for an address unless it is a new build assessment. This can mean that opportunities to identify an incorrect address are missed for new build assessments.
f. Homes with very high Heat Transfer Coefficients should be flagged as potential errors before being lodged in the EPC Register.

Modelling assumptions for EPCs (generated by either SAP or HEM)

g. Assumptions about 2-zone heating should be reviewed in SAP and given consideration in HEM, as well as the impacts that space heating zonal controls have on internal temperature.
h. The electricity demand and seasonal variation for lights and appliances should be reviewed for SAP and given consideration in HEM.
i. The assumptions used for the calculation of the building heat transfer coefficient need to be reviewed, particularly for RdSAP and HEM development.
j. The minimum ventilation of 0.5 ach in SAP should be reviewed, and given consideration for HEM.

Validation and Quality assurance

k. The EPC Accuracy project has demonstrated that energy models such as HEM could be tested for their validity using an energy signature method[2] related to Smart Meter Enabled Thermal Energy Ratings (SMETER). As well as the energy signatures used in this study to disaggregate energy use for different purposes, methods could also be developed using diurnal signatures which could be useful when validating half hourly models such as HEM.
l. Better empirical evidence of in-use ventilation rates could support the development and validation of ventilation rate models as used in HEM where improvements have already been made3.
m. Model validation should be an on-going process. This is because energy models and their assumptions represent a rapidly evolving socio-technical system. Lessons learnt from this project suggest an annual comparison between EPC modelled and measured monthly data is now feasible using smart meter and other administrative data. This means that changes to domestic energy use over time and the impact of these on agreement between metered and modelled energy use can be tracked, for example due to changes in technology prevalence and use (e.g. heat pumps, batteries, air conditioning), societal-level shifts (e.g. prevalence of working from home during the pandemic, energy price shocks, or the potential future influence of time-of-use tariffs), or changes to weather

[2] The energy signature is an analysis method for analysing the relationship between external temperature and energy use.
[3] https://www.gov.uk/government/publications/gathering-evidence-to-improve-airtightness-in-the-uk-housing-stock

conditions. Similarly, the effect of future changes in EPC processes, the relevant policy landscape, or model assumptions can also be tracked. This would prevent delays in identification and rectification of emerging discrepancies.

n. Development of a fully calibrated longitudinal baseline comparison tool (modelled EPC from SAP/HEM alongside metered energy demand) against which developments to the EPC process can be assessed.
o. Recruitment and maintenance of a sample of groups of homes which are under-represented in the stock but are of special interest, e.g. new build homes, homes with heat pumps, and a group of the least efficient homes. Unless these types of homes are specifically recruited to increase sample sizes it is difficult to provide deep analysis of their performance.
p. NBM is a key policy and research tool for the use of SAP/HEM; a strong NBM user group both within and outside government would help to develop the tool and increase the capability to validate and quality control building energy models.

The analysis of electrically heated homes was significantly more limited than for gas heated homes, limiting the findings and conclusions that could be drawn. Further research in this area would be beneficial. The analysis focuses on comparing monitored with modelled energy and internal temperature data for three main samples of homes: 43 electrically heated, smart-metered SERL Observatory homes; 31 electrically heated Energy Follow-up-Survey (EFUS) homes with monitored internal temperature data; and four electrically heated SERL homes that have been resurveyed by an expert assessor as part of a forensic investigation. This analysis focussed on conventional electric heating systems and excluded homes with heat pumps.

Key findings relating to the analysis of electrically heated homes include:

- Electrically heated homes make up less than 10% of UK homes, and therefore a small percentage of nationally representative samples such as EHS and SERL. Therefore, analysis of this group of homes is far less conclusive than for gas heated homes. Also, electrically heated homes are more challenging to analyse because they normally use one fuel, making it more difficult to disaggregate energy use for heating from other energy uses such as lights and appliances.
- On average, electrically heated homes in the SERL Observatory use 40% of the energy that gas heated homes do, in part because they are 80% of the size of gas heated homes. After normalising by floor area electrically heated homes have half the energy use intensity of gas heated homes, this is likely because they are often flats which have smaller heat loss than more detached properties, and they are 0.39°C cooler during the heating season.
- Electrically heated homes have a lower SAP Energy Efficiency Rating (EER) and EPC band, often F & G (unless heated by heat pumps which is not the focus of this study). This is because EER is based on fuel cost, and the standard electricity tariff is about 4 times more expensive than gas. So, although an electrically heated home may use half the energy, its heating costs can be twice that of a gas heated home.
- Electrically heated homes, like gas heated homes, generally use less energy than SAP models predict. However, the performance gap in metered to modelled energy demand

is much greater. The mean difference between metered and modelled energy use for electrically heated homes is -31.4% compared to -16.0% for gas heated homes. Like gas heated homes the discrepancy is largest in the winter, to a maximum of -47% in December (i.e. homes use almost half the expected energy), the discrepancy remains large in the summer with the smallest gap being -20% in July.

- The increased performance gap may be due in part to the additional complexity in modelling electrically heated homes, in particular related to the responsiveness of the heating system and the type of heat transfer and the impact of this on mean internal temperature.
- Electrically heated homes also have an added complexity with regards to the cost based EER score because of electricity having different tariffs depending on the time of use. For example, homes with some types of storage heaters are assumed to provide 20% of their space heating energy from on-peak electricity use which can be 2.8 times more expensive than off-peak electricity.
- Electrically heated homes are on average slightly cooler than modelled, and measured data indicates that electrically heated homes may be thermally 'zoned' in a way that gas heated homes are not. Although the SAP model overestimates the non-living space (Zone 2) temperature reduction, the measured Mean Internal Temperature (MIT) is cooler than the modelled MIT, suggesting that underheating may contribute to the EPC performance gap in these homes. Forensic investigation of four SERL homes that had an expert full SAP calculation suggests that there is a much larger difference between the original EPC assessor RdSAP EER rating and the expert full SAP EER rating than is the case with gas heated homes. Unlike gas heated homes, 3 of the expert assessments indicated that the original RdSAP assessment EER rating was significantly higher (gave a better score) than that calculated by the expert.

Glossary/acronyms

Balance Temperature: The external temperature below which heating is used in the PTG model.

Base Power: The power used in the summer, assumed to be a constant in the PTG model.

BREDEM - Building Research Establishment Domestic Energy Model: the core calculation underpinning SAP.

EDOL – Energy Demand Observatory and Laboratory: An EPSRC funded project which builds on SERL, which monitors temperature and high-resolution energy use in 2000 of the SERL Observatory homes. Further subsets of homes will be recruited into specific ‘laboratories’ for deeper analysis related to specific issues or technologies (e.g. heat pumps or EVs)

EER - Energy Efficiency Rating: a number (the SAP number) which is then converted to an A to G band. EER is calculated from the annual regulated fuel cost per meter squared of floor area. The EER is calculated using national not regional weather data. EPCs also display an Environmental Impact Rating see EIR.

EFUS - Energy Follow-up Survey: A follow-up study to the EHS focussing on domestic energy use for a subset of homes last completed in 2019. The study includes a detailed, energy-focussed questionnaire, indoor temperature monitoring in the living room and main bedroom for a subset of homes, and some hourly/half hourly electricity and gas metering in a further subset of homes.

EHS - English Housing Survey: A nationally representative survey of English homes. The study includes a questionnaire relating to many aspects of the building conditions and socioeconomic status of the residents.

EIR - Environmental Impact Rating: calculated from the carbon emissions of the home and is also displayed as an A to G rating on the EPC certificate.

Energy Signature: See PTG

EPC Registry - a centralised publicly accessible database where all EPCs are lodged including some of the key variables used to calculate an EPC such as floor area, efficiency of walls, windows, etc.

EUI – Energy Use intensity: Energy use normalised by floor area.

GHG - Green Homes Grant: UK government initiative launched in September 2020 to improve the energy efficiency of homes in England and help reduce carbon emissions. It aimed to encourage homeowners and landlords to install energy-saving measures by providing financial support.

GHG-SMETER – Green Homes Grant-Smart Meter Enabled Thermal Efficiency Ratings: Approximately 2500 of the homes that received GHG financing were recruited to the GHG-SMETER evaluation project. Smart meter data and surveys covering sociotechnical information were collected for all homes, and a subset of 200 had internal temperature and energy use monitored to help test the validity of SMETER techniques - an innovative approach to using smart meter data to measure the in-use HTC.

HLP - Heat Loss Parameter (W/m^2K): The HTC normalised by the floor area.

HPLC - Heat Power Loss Coefficient (W/K): The HTC divided by the heating system efficiency. This parameter represents the amount of delivered energy required to change the internal temperature by 1C.

HPLP – Heat Power Loss Parameter (W/m^2K): The HPLC normalised by floor area.

HTC - Heat Transfer Coefficient (W/K): This parameter represents the fabric and ventilation heat transfer per degree of temperature difference between the indoor and outdoor environment. N.B. This parameter was historically known as the HLC – heat loss coefficient, however HTC is now preferred to cover use in both heating and cooling contexts.

MIT - Mean Internal Temperature (C): The mean of the internal temperature. This is a key parameter for the SAP model as the temperature difference between the MIT and external temperature drives the expected energy use for heating.

NBM – National Building Model: a government owned model used to assess housing stock characteristics, energy performance and the impact of various policies on housing, energy consumption and carbon emissions. Its core calculation is based on BREDEM including calculating the SAP rating for the stock of homes.

NEED - National Energy Efficiency Data-framework: a database covering properties in Great Britain which links together existing data sources, and provides insight on factors affecting household energy consumption and the consumption savings resulting from installation of government supported energy efficiency measures. It combines data on energy consumption, property attributes, household characteristics and energy efficiency measures installed through government schemes.

NHM - National Housing Model: the precursor name to the current National Building Model (NBM)

Performance Gap - $\Delta EUI\% = \frac{EUI_{metered} - EUI_{modelled}}{EUI_{modelled}} \times 100$

PEUI – Primary Energy Use Intensity (kWh/m^2): the energy generated (rather than delivered) normalised by floor area. This takes into account generation/ transmission losses for electricity and pipe losses for gas. For EPCs this typically means that electricity is weighted about 3 times more than gas. This is the only energy metric available in the public EPC registry.

PTG - Power Temperature Gradient: An analysis method for energy use in buildings. The model assumes constant power use in the summer and a linear increase in power use below a threshold external temperature known as the balance temperature. This model is also known as an energy signature.

RdSAP - Reduced Data Standard Assessment Procedure: a simplified version of SAP used for existing buildings when full building characteristics are not known. This model relies on a series of default assumptions when details of the building cannot be easily surmised.

SAP - Standard Assessment Procedure: a normative model of domestic energy use which underlies the EPC process in the UK.

SERL - Smart Energy Research Lab: originally an EPSRC-funded research project aiming to recruit 10,000 households and create a database of their smart meter data linked to other datasets including their EPCs, local weather conditions and sociotechnical information collected via participant surveys. SERL successfully recruited 13,000 participants and continues to collect their smart meter data on a longitudinal basis from 2018 to present.

SIT - Standardised Internal Temperature: The Mean Internal temperature at a standardised external temperature. In this report data has been standardised to an external temperature of 7C which is approximately the mean heating season external temperature used in the SAP calculation.

UPRN – Unique Property Reference Number: a code which uniquely identifies addresses in Great Britain.

Prologue

Although SAP can appear a simple fully documented model, it is a complicated model of a complex socio-technical system, which is often applied to answer questions beyond its original design. We often forget what question a SAP rating of 42 is the answer to. SAP was not designed to calculate the actual energy consumption of a house with a specific occupant but to allow comparison between two homes to determine which would be the most efficient under standard occupancy. We hope this report provides additional insight and evidence into what questions EPCs are accurately producing an answer to. We should also not forget the following quote while reading this report.

"All models are wrong, but some are useful", George Box

We often feel that it is only building energy models that are wrong, we hope our research helps to make EPCs more useful.

Part 1: Gas heated homes

Introduction

Energy Performance Certificates (EPCs) were introduced in 2007 to increase consumer awareness of building energy efficiency, and since their launch over 27 million domestic EPC records have been generated in England and Wales[4]. EPCs are increasingly used to support the net zero transition: 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), and the UK government has an aspiration that all homes, where feasible, achieve EPC-C by 2035. EPCs are not intended to give a prediction of the actual energy use of a particular home as they assume normative consumption and only consider certain 'regulated' uses. However, to be as effective as possible given their current uses, they should provide a reasonably accurate measure of the difference in efficiency between buildings and the potential benefit of energy efficiency retrofit measures.

The model underlying the EPC is the Standard Assessment Procedure (SAP). SAP uses factors relating to the physical building, internal systems, and assumptions regarding the occupancy and heating schedule to calculate the 'regulated' energy use of the building (energy for space and water heating and associated fans, pumps and controls, and fixed lighting). SAP includes algorithms for calculating unregulated energy use (appliances and cooking), but these energy uses are excluded from the EPC rating. EPCs are generated for most new homes using a full SAP procedure, whereby an energy assessor gathers detailed information on the building (from planning drawings, specification documents, etc.) as inputs to the SAP model. However, since the same level of detailed information may not be readily available for existing buildings, existing building EPCs are typically generated using a Reduced data SAP (RdSAP) process. RdSAP defines defaults and conventions for model inputs based on observable characteristics of the building (such as its age). When EPCs are generated for existing buildings, they are almost always produced using RdSAP. These existing homes make up the majority of homes that need to retrofitted to be Net Zero by 2050 to reach the UK's climate goals.

For many years there has been anecdotal and growing empirical evidence of a significant gap between EPC-modelled and metered energy use.

[4] MHCLG, Live tables on Energy Performance of Buildings Certificates (accessed 30th April 2025)

Recent research by the authors[5] using data from a representative sample of GB homes (the Smart Energy Research Lab [SERL] Observatory) has, for the first time, rigorously quantified the size of the gap in gas heated homes (see Figure 1 below):

- EPC F- and G-rated homes are predicted to use 50% more energy use than metered.
- There is little difference in metered energy use between bands D to G rated homes.
- The gap cannot be solely explained by SAP assumed occupant behaviour.

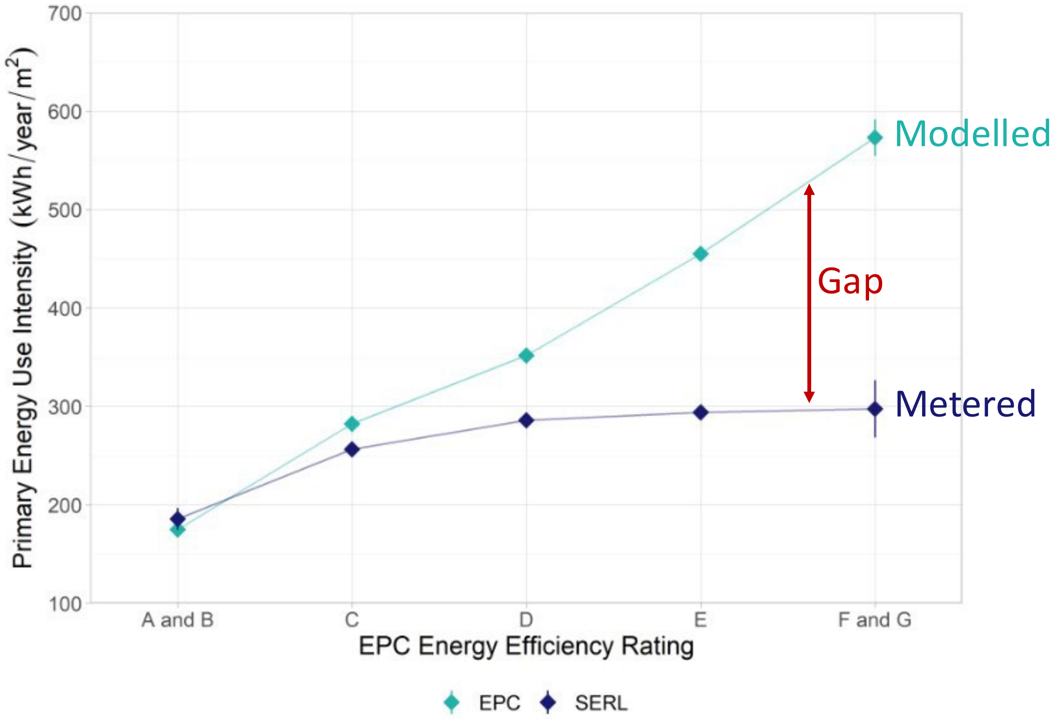

Figure 1 Comparison of metered and EPC-modelled primary energy use intensity, showing that EPCs increasingly overpredict energy use as EPC band worsens.

A random error in the EPC model would mean that the accuracy of any individual home's rating would be uncertain. However, more problematic would be a systematic error, which would mean that there is a consistent skew in the difference between EPC modelled and metered energy use. Our research indicates that there is a systematic error in the EPC rating: homes that are rated as less efficient consistently use far less energy than the EPC model predicts.

There are many hypotheses for the gap, they broadly fit into three interconnected potential sources of error. Errors in the core calculation, errors in the inputs and assumptions used in the calculations, and errors associated with the process of collecting the input data for the EPC. Examples of hypothesised causes of the gap include:

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[5] Few, J. et al. (2023) 'The over-prediction of primary energy use intensity by EPCs in Great Britain: A direct comparison of EPC-modelled and smart metered energy use in gas- heated homes', *Energy and Buildings*, 288. doi: 10.1016/j.enbuild.2023.113024.

1. Core Calculation

   Mean Internal Temperatures (MIT) is calculated within SAP for the living room (zone 1) and the rest of the house (Zone 2) from the demand temperature, hours of heating building heat loss, incidental gains and controls. The MIT is a key input into the space heating energy use calculation, and it may not be modelled correctly with changing energy efficiency.
   Heating system and controls: model simplification, e.g. no impact of heating or radiator size, no modelling of heating system modulation, modelling of controls which are assumed to have a set impact.

2. Inputs & Assumptions

   Heat loss: overestimation of the heat loss from uninsulated properties and underestimation of the heat loss of well insulated properties. Solid walls, floor insulation and ventilation heat loss assumptions may be a key source of this error.
   Heating profiles - 24hr and weekend-weekday: there is some evidence that over time the difference between weekend and weekday heating has reduced, as recent evidence shows little difference in energy use between weekends and weekdays[6].
   Occupancy, hot water, and lights & appliance assumptions may be outdated.

3. EPC Process

   Out-dated EPCs: the EPC Registry contains historic EPCs calculated using different vintages of SAP/RdSAP, with different modelling conventions and assumptions. Older EPCs are more likely to have been created using outdated assumptions. Also, homes may have had efficiency upgrades since EPC rating (e.g. replacement boilers and windows), if the EPC has not been updated it will report poorer performance than appropriate for the building post-upgrade.
   RdSAP vs SAP: Motivation & Defaults: EPC assessors may be incentivised by the process and by those commissioning EPCs. Existing homes may be pessimistically rated due to the use of defaults in RdSAP (the 'Default Effect' and 'Fear of Audit' effects) whereas new homes maybe optimistic due to use of ideal values and assumed construction without error or deviation.

Evidence for the above hypotheses is often anecdotal or limited to a small number of case-study sites. This report produces a more systematic analysis to examine the cause of the gap using data from several hundred homes collected by the SERL team, and other secondary data.

The SERL Observatory provides a unique data set which can help identify the cause of EPC errors. SERL provides a large sample of homes (13,000+) compared to many other energy datasets, see Figure 2 below. For each home, contextual data such as self-reported thermostat settings and occupant numbers are available, allowing detailed comparison with the standard SAP assumptions. Significantly, the energy data collected in SERL is half-hourly, not annual, allowing direct comparison between monthly SAP predictions and monthly measurements for

[6] Few, J. et al. (2024) 'Smart Energy Research Lab: Energy use in GB domestic buildings 2022 and 2023', *Smart Energy Research Lab (SERL) Statistical Reports*, 2. URL: https://serl.ac.uk/key-documents/reports/

the first time. This helps identify how much of the performance gap is attributed to summer energy use (e.g. lights, appliances, and hot water), compared to space heating during the winter. The fact that the smart meter data is combined with contextual data enables a more direct comparison of meter data to SAP modelled data. For example, it is possible to eliminate homes that use unmetered energy (e.g. oil and LPG), and to calculate unregulated energy use based on occupancy predicted from floor area.

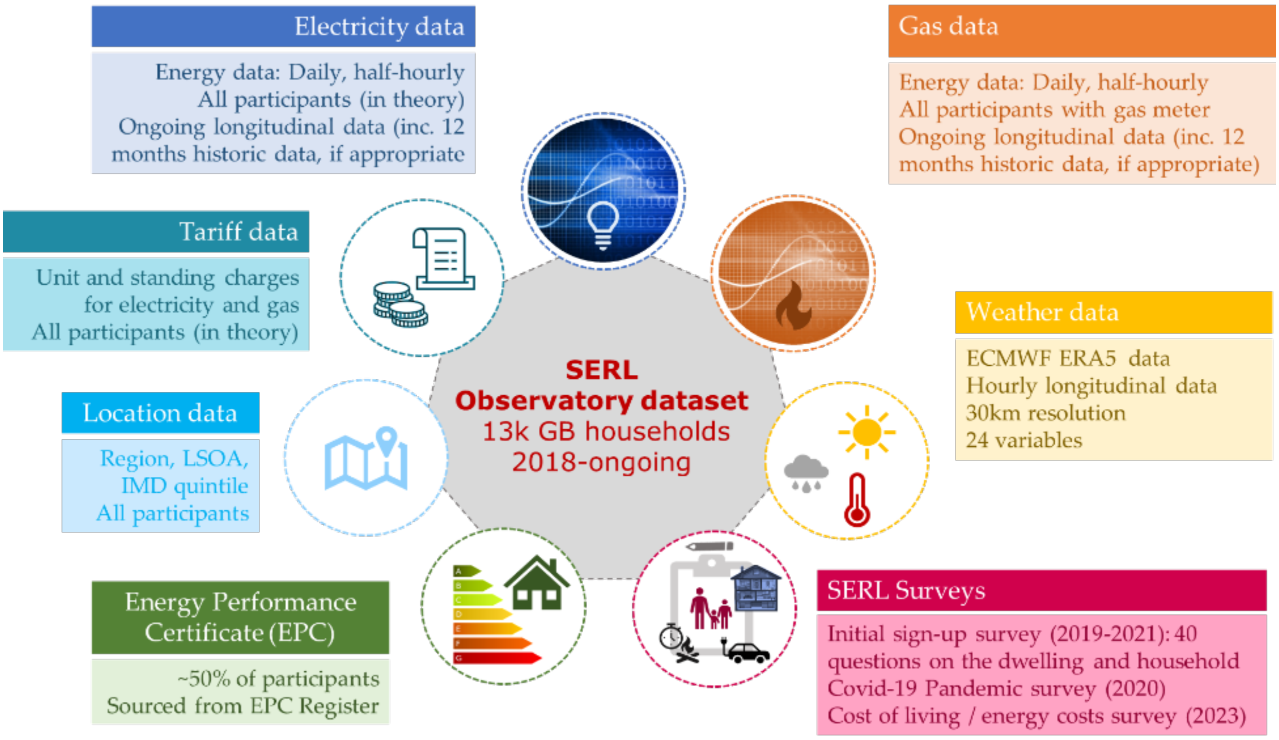

Figure 2 Summary of the SERL Observatory Dataset

Most users of the EPC are primarily interested in the Energy Efficiency Rating (EER) value, as this determines the main EPC banding. For this reason, we present many of our results in terms of how big the gap between measured and modelled energy use for varying EER bands. However, the definition of the EER is complicated as it is a non-linear function of regulated fuel costs which can make the results difficult to interpret. For example, a gas heated home typically uses approximately four times more gas than electricity, but since electricity is roughly four times more expensive than gas the electricity cost of running a home can be similar to the gas cost. SAP does not calculate the appliance energy cost, yet it assumes the appliance energy use offsets space heating energy use via incidental heat gains. Due to these types of complications, in addition to presenting results in terms of the how they vary with EER value we also present results in terms of how they vary with physical attributes of a building such as its heat loss, or space heating system efficiency. Also, the results presented in the report are for total energy use, not just regulated energy use, i.e. our modelled energy results include appliance and cooking modelled energy use so that they can be compared with the meter data on a like-for-like basis.

This part of the report exclusively focuses on homes where gas central heating is the main form of heating, Part 2 focuses on electrically heated homes.

Research Questions[7]

RQ1. How does the SAP model (including through the modelling of heat loss, ventilation, internal temperatures and summer energy use) impact the accuracy of EPCs?

RQ2. How does the RdSAP process, through its use of defaults and changing conventions over time, affect the accuracy of EPCs? And how does this differ from the full SAP process?

RQ3. How does the motivation of assessors impact the accuracy of EPCs?

RQ4. What additional factors significantly impact the accuracy of EPCs?

Background and Literature review

This section provides the background and reviews some of the key literature regarding the:

- History and evolution of SAP and the EPC process
- Other national and international evidence that demonstrates an EPC performance gap.
- Empirical and theoretical evidence of potential causes of a gap

This review is not comprehensive as much of the evidence behind the evolution of SAP and EPCs has historically been incorporated in a range of non-public documents and much of the UK energy and domestic building research over the last three decades provides some evidence related to this issue.

A history of SAP and EPCs

The Standard Assessment Procedure (SAP) was first published in 1993 and has since been updated periodically, in 1998, 2001, 2005, 2009, 2012, and most recently in 2022. In 1994, SAP was first cited in the Building Regulations as the means of assessing the energy performance of dwellings. In 2007 it was adopted as the methodology behind Energy Performance Certificates (EPCs). Table 1 below provides a summary of the SAP and RdSAP versions and key changes.

[7] The original research questions are listed in the EPC tender, but in this report they have been slightly restructured to group similar themes in the analysis

Table 1 Key dates and changes associated with versions of SAP and RdSAP

Document	Came into force	Notes
SAP 1995 - original SAP		
SAP 1998	For new building regulations	
SAP 2001	For new building regulations	
SAP 2005	For new building regulations	
RdSAP 9.80	August 2007	
RdSAP 9.82	September 2008	Introduced cob walls, include floors and thatched roofs in assessment
RdSAP 9.83	October 2009	Introduction of RdSAP conventions
SAP 2009	October 2010	
RdSAP 9.90	April 2011	Can have 2 main heating systems. Enter kWp for PV systems. Can have up to 4 extensions.
RdSAP 9.91	April 2012 (E&W, NI), Oct 2012 (SC). In preparation for the Green Deal introduced in Jan 2013	Can specify specific insulation products using the 'overwriting u-value' functionality
SAP 2012	July 2014 E&W and October 2015 Scotland for new building regulations	Allow calculations using regional weather, and height above sea level incorporated into external temperature. CO2 emissions factors, fuel prices and primary energy factors extensively revised. Extended options for heat loss from pipework.
RdSAP 9.92	December 2014	Party walls updated – modern cavity party walls assumed to have heat loss unless insulated. Old solid party walls have no heat loss. Additional heating control options added.
RdSAP 9.93	November 2017	U-values revised for pre-1975 walls, party wall recommendation.
RdSAP 2012 v9.94	September 2019	Appendix Q introduced – allowing individual branded products to be included in the calculation with specific performance values determined by a product test. Assessors must confirm why an EPC is being generated if an EPC already exists.
SAP10.2	June 2022	CO2 emission factors, fuel prices, primary energy factors all updated.
RdSAP10.2		Measure all windows, additional measurements to capture different construction types of walls and gable walls. 2023 onwards age band introduced. Isle of Mann added as a region. PV diverts and battery storage can be accounted for. Pressure testing can be included.

The SAP calculation evolved from the Building Research Establishment Domestic Energy Model (BREDEM) which was converted to an energy rating tool via the Milton Keynes Energy Cost Index[8] and the National Home Energy Rating System (NHER) before it became SAP. Much of the original philosophy underpinning SAP, RdSAP and EPCs today was laid out in the development of these historic tools including that the rating should:

- Be an asset rating to allow comparison of the likely energy consumption between houses at the point of purchase or rent. Like the miles per gallon rating for cars, this would assume a normative occupant behaviour and so not say how much user A would consume in home B.
- Be a rating based on fuel cost – as this is what homeowners understood.
- Be a rating which could be applied to both new and existing homes.

[8] Chapman, P. The Milton Keynes Energy Cost Index, Energy and Buildings, 14 (190) 83-101

- Be a calculation which could be undertaken without a computer because this meant that everybody could undertake the calculation (not everybody had access to computers when it was developed) and so all assumptions were transparent in the calculation.
- Include only factors that had significant impact on energy use were incorporated.
- Include only factors that could easily/cost effectively be measured in a building were incorporated.
- Balance increased accuracy from additional complexity with increased user error in collecting additional information.

The original aims of SAP were very clear, i.e. to provide an energy rating for home-owners or tenants to compare one house with another. This seemingly straightforward aim interacts with several potentially political issues. For example, whether a home should receive a worse rating because it is large and therefore uses more energy, or because it is in colder region and therefore uses more energy, and whether standing charges and appliance use should be included in running costs used in the calculations. Alongside this original aim, SAP and EPCs have subsequently been used for many purposes they were not originally designed for, including as policy and research tools. The energy policy landscape has also changed over time with shifting priorities around affordability, security of supply, and decarbonisation. Moreover, the normative assumptions regarding occupancy were based on typical expectations in the 80s and 90s which may have changed in the intervening decades, and some empirical elements of the calculation were generated for buildings of that era.

The changing use cases as well as advances in modelling and empirical data collection have resulted in proposed improvements to the EPC process via an EPC Action Plan[9], as well as new core calculation method called the Home Energy Model (HEM)[10]. Assumptions for HEM are built into various wrappers for different applications such as regulatory control (FHS wrapper) and EPC rating. There is now an opportunity to review many of the assumptions to improve both the accuracy and the usefulness of the model outcomes. This report aims to provide empirical evidence to feed into the development of the core calculation, wrappers and the wider EPC process.

The SAP model

The core model underpinning SAP has been BREDEM (BRE-Domestic Energy Model) which was originally an annual degree-day calculation incorporating a modified degree-day base temperature. This was subsequently updated into a monthly pseudo-steady state calculation. The main difference between BREDEM and SAP was that SAP was a constrained version of BREDEM that assumed fixed occupancy and behaviour. The main assumptions include an assumed number of occupants based on the floor area, hot water use per occupant, appliance use per occupant, demand temperature in different zones of the house, hours of heating,

[9] Improving Energy Performance Certificates: action plan – progress report, 8th November 2021,
[10] Home Energy Model: replacement for the Standard Assessment Procedure (SAP), 13th December 2023.

whether the whole house was heated, and the proportion of secondary heating use (if applicable).

Although SAP has simple building physics equations at its core, it has evolved to cope with new technologies and building characteristics. This has significantly increased the complexity, and many assumptions are buried in the algorithms that have not been sufficiently documented and have unclear supporting empirical evidence.

Validation, Calibration and Sensitivity of SAP

BREDEM, and hence SAP, has undergone a series of exercises comparing modelled data with measured data and then using the results of these to help calibrate some of the assumptions and improve algorithms within the model. Originally BREDEM was tested against 42 existing homes occupied by BRE staff, in 1982[11]. Much of the later detailed validation focused on new buildings in Milton Keynes (Pennyland[12]- 177 homes, Linford[13]-8 homes, and the Milton Keynes Energy Park[14], 160 homes) to support the development of new Building Regulations. New homes are easier to monitor as monitoring equipment can be installed during construction, however the vast majority of the stock is existing buildings. More recently comparison with empirical data from the Energy Follow up Survey (EFUS) of the English Housing Survey (EHS) and annualised National Energy Efficiency Database (NEED) data has been used to test the validity of SAP/BREDEM. These data sets either have small sample sizes with much contextual data or large sample sizes with poor contextual data, both of which make it challenging to draw firm conclusions that are not at the population or stock level.

Inter-model comparisons have also been undertaken historically with Passive House Planning Package (PHPP)[15] and simulation models such as SERI-RES and ESP-r. The main conclusions from these analyses is often that the main difference is less to do with the core model but more the assumptions. This is in part because all building physics models have at their core the conservation of energy.

Several sensitivity analyses[16],[17] have been undertaken to look at the key parameters that impact the SAP value or EPC rating. Most of these have focused on input parameters rather

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[11] 1982Uglow CE. Energy use in dwellings: An exercise to investigate the validity of a simple calculation method. Building Services Engineering Research and Technology. 1982;3(1):35-39. doi:10.1177/014362448200300105
[12] Chapman, J.; Lowe, R. and Everett, R. (1985). The Pennyland Project. ERG Report 53; Energy Research Group, The Open University, Milton Keynes, UK.
[13] Everett, M.; Horton, A; Doggart, J and Willoughby, J (1985). Linford Low Energy Houses. ERG Report 50; Energy Research Group, The Open University, Milton Keynes, UK.
[14] A.J. Summerfield, R.J. Lowe, H.R. Bruhns, J.A. Caeiro, J.P. Steadman, T. Oreszczyn, Milton Keynes Energy Park revisited: Changes in internal temperatures and energy usage, Energy and Buildings, Volume 39, Issue 7, 2007, Pages 783-791,ISSN 0378-7788,
[15] AECB, "Projecting Energy Use and CO2 emissions from Low Energy Buildings: A comparison of PHPP with SAP
[16] Hughes, M., Palmer, J., Cheng, V., & Shipworth, D. (2013). Sensitivity and uncertainty analysis of England's housing energy model. Building Research & Information, 41(2), 156–167. https://doi.org/10.1080/09613218.2013.769146
[17] Stone, A., Shipworth, D., Biddulph, P., & Oreszczyn, T. (2014). Key factors determining the energy rating of existing English houses. Building Research & Information, 42(6), 725–738. https://doi.org/10.1080/09613218.2014.905383

than core algorithms. Table 2 below shows the results from the sensitivity analysis by Stone et al (2014), who found that "the largest contribution to the observed variance in energy rating are geometry, heating system efficiency and external wall U-value. Together these account for just over 75% of the variance in energy rating".

Table 2 First order and total sensitivity coefficients for Energy Efficiency Rating (EER) and Environmental Impact Rating (EIR) from Stone et al (2014)

Factor	EER		EIR	
	S_i	S_t	S_i	S_t
main system efficiency	0.3157	0.3236	0.3308	0.3326
U-value external wall	0.2305	0.2548	0.2394	0.2571
geometry	0.2199	0.2641	0.2195	0.2508
U-value roof	0.0768	0.0979	0.0745	0.0883
thermal_mass_parameter	0.0184	0.0214	0.0170	0.0186
U-value ground floor	0.0158	0.0183	0.0176	0.0196
hw_cylinder_insulation	0.0145	0.0131	0.0135	0.0128
glazing type	0.0109	0.0138	0.0109	0.0136
heating_control_type	0.0096	0.0133	0.0115	0.0137
temperature_adjustment	0.0074	0.0078	0.0065	0.0070
low_energy_bulb_ratio	0.0055	0.0055	0.0024	0.0026
has_cylinderstat	0.0040	0.0059	0.0044	0.0060
hw_cylinder_insulation_type	0.0038	0.0052	0.0039	0.0054
Nfansandpassivevents	0.0022	0.0015	0.0022	0.0016
Nflues	0.0022	0.0027	0.0019	0.0029
floor_infiltration	0.0011	0.0011	0.0016	0.0012
hw_cylinder_volume	0.0009	0.0023	0.0011	0.0022
frame_factor	0.0002	0.0002	0.0002	0.0002
Nfluelessgasfires	0.0001	0.0001	0.0001	0.0001
Total	0.9394	1.0524	0.9590	1.0363

The RdSAP and full SAP processes

Reduced data SAP (RdSAP) was introduced in 2005 as a simpler and lower cost method for assessing existing dwellings. An RdSAP assessment will use a set of assumptions about the dwelling, reducing the volume of data an energy assessor must collect. There have been three main versions of RdSAP 2012 Version 9.92 effective till 19th Nov 2017 when 9.93 was introduced and then 9.94 which was introduced on 22nd September 2019. RdSAP10 is expected to become the approved method of EPC calculation soon and, where practical, insights from this research have been applied to the new RdSAP-10 process and calculation.

This report focuses on RdSAP 2012, which has had three different versions. In addition to these versions, different conventions[18] have been specified over time, which assessors use when collecting the input data for a RdSAP calculation, and different fuel prices and technology

[18] https://bregroup.com/documents/d/bre-group/rdsap-conventions-11_4-from-01-jul-2024-

efficiencies can be applied to parts of the EPC calculation via the monthly updated Products Characteristic Database (PCDB)[19] .

The application of RdSAP conventions could have a significant impact on the performance gap. For example, many conventions relate to extensions or conversions of a building such as room-in-roof. The default is to use the property age of the original building to determine the U-values of the construction, unless the occupants have proof that a conversion has changed the U-values. In most cases, conversions or extensions will have better thermal performance than the original building but the homeowners may not have proof. Since older less insulated properties are more likely to have more extensions than new homes this convention may impact the performance gap disproportionally in older properties. There may be significant additional burden for an EPC assessor, which could affect the outcomes, when carrying out an assessment of an older building with different wall types, room in roof, basement or conservatories compared to a newer regular shaped building with no conversions or extensions.

The EPC energy performance gap: a pan-European problem?

There is extensive evidence from across Europe regarding the difference between EPC-modelled energy use and actual metered energy use, for example, the Netherlands (van den Brom et al., 2018[20]), Poland (Szulgowska-Zgrzywa et al., 2020[21]), and Serbia (Anđelković et al., 2021[22]), see Figure 3 below for analysis from the Netherlands. There are several common findings in this research. Firstly, overall, the modelled energy use is greater than the metered energy use. Secondly, the most energy-efficient homes frequently use more energy than predicted. Thirdly, the least energy efficient homes use far less energy than predicted. The combination of the second and third points means that the metered energy results show a much shallower change in energy use between band ratings than predicted. For example, in the UK, Summerfield et al. (2019)[23] show that across all EPC bands the metered gas consumption is almost always within the range estimated for EPC band C.

[19] https://www.ncm-pcdb.org.uk/sap/searchpod.jsp?id=17
[20] van den Brom, P., Meijer, A. and Visscher, H. (2018) ‘Performance gaps in energy consumption: household groups and building characteristics’, *Building Research and Information*, 46(1), pp. 54–70. doi: 10.1080/09613218.2017.1312897.
[21] Szulgowska-Zgrzywa, M. et al. (2020) ‘Impact of users’ behavior and real weather conditions on the energy consumption of tenement houses in Wroclaw, Poland: Energy performance gap simulation based on a model calibrated by field measurements’, *Energies*, 13(24). doi: 10.3390/en13246707.
[22] Anđelković, A. S. et al. (2021) ‘Building energy performance certificate—a relevant indicator of actual energy consumption and savings?’, *Energies*, 14(12). doi: 10.3390/en14123455.
[23] Summerfield, A. J. et al. (2019) ‘What do empirical findings reveal about modelled energy demand and energy ratings? Comparisons of gas consumption across the English residential sector’, Energy Policy, 129(March), pp. 997–1007. doi: 10.1016/j.enpol.2019.02.033.

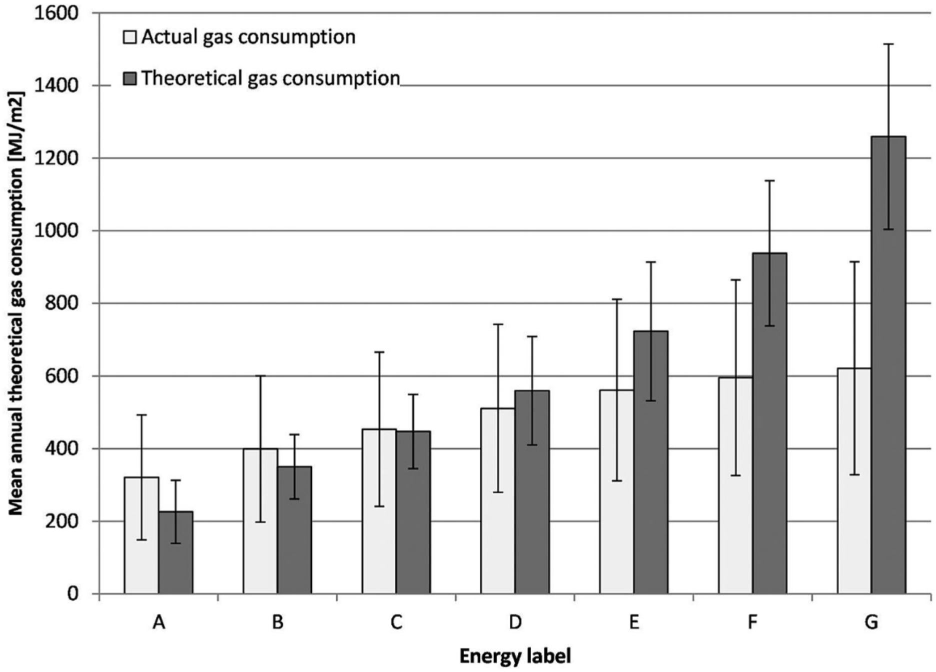

Figure 3 Netherlands EPC performance gap in 1.4 million social houses, comparison of actual versus theoretical gas consumption (from van Brom et al., 2018)

One complication in such comparisons is that the energy use reported by EPCs is not the total energy consumption, but the regulated energy use which includes energy use related to space and water heating (and sometimes lighting, as in the UK), but excludes appliances and cooking. This means that the metered energy consumption is not directly comparable to the energy consumption reported by the EPC (Coyne and Denny, 2021[24]; Van Hove et al., 2022[25]). In some research this is presented as a known (and uncorrected) systematic bias towards lower modelled energy use compared to expected total energy use (Van Hove et al., 2022), while in others an estimation of the 'missing' energy use is provided and used to adjust either the metered or modelled energy use (Coyne and Denny, 2021).

The problem above is compounded by the potential inclusion of homes which use unmetered forms of energy, such as oil boilers or wood-burning stoves. Much previous analysis (e.g. Summerfield et al., 2019; Coyne and Denny, 2021; Van Hove et al., 2022) has used data which does not record whether homes were using unmetered energy and therefore whether the metered energy use accurately reflects the total energy consumption of the home. In the UK, the EPC EER band rating is based on fuel cost, meaning that F and G homes are more likely to be heated by more expensive fuels such as LPG and oil. These fuels are also unmetered which may partially explain the large discrepancies between SAP calculations and metered energy use in low efficiency bands.

[24] Coyne, B. and Denny, E. (2021) 'Mind the Energy Performance Gap: testing the accuracy of building Energy Performance Certificates in Ireland', *Energy Efficiency*, 14(6). doi: 10.1007/s12053-021-09960-1.
[25] Van Hove, M. Y. C. et al. (2022) 'Large-scale statistical analysis and modelling of real and regulatory total energy use in existing single-family houses in Flanders', *Building Research and Information*. doi: 10.1080/09613218.2022.2113023.

The European Union Energy Performance of Buildings Directive (EPBD) mandates that all European countries should have an EPC at the point of sale or rent of a property. However, each country has freedom to decide what the rating covers, how it is practically implemented and calculated and the assumptions that underpin the calculation. This makes direct comparison between countries challenging; nonetheless, all countries must report the Primary Energy use Intensity (PEUI) and several countries (Austria, Germany, Netherlands, Denmark and Ireland) have reported a comparison between metered and modelled performance gap (Ref). Figure 4 below is a comparison between a GB study (Few et al., 2023) and analysis of Irish EPCs (Coyne and Denny, 2021), Ireland adopted a similar EPC system to GB. The overall trends are extremely similar, although there is a difference in the correction methods used for appliances and cooking in the below comparison.

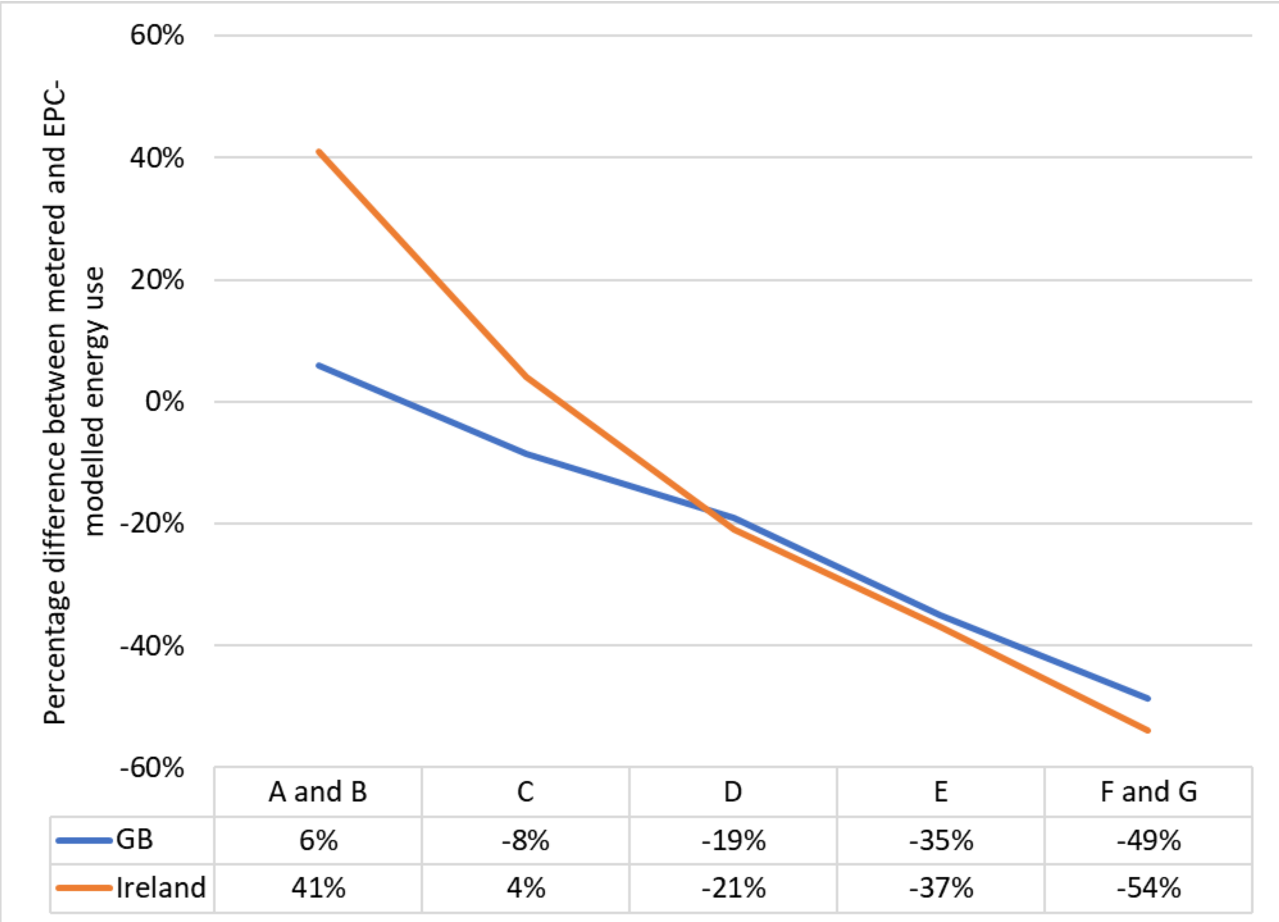

Figure 4 Percentage difference between metered energy and EPC predicted energy [(metered-EPC)/EPC] source of data Few et al. (2023) for GB and Coyne and Denny (2021) for Ireland.

Across Europe the price of an EPC for a single-family house varies over an order of magnitude, in part due to the level of data collection required in a property, see Figure 5. England and Scotland have one of the lowest prices. In some countries like the Netherlands EPCs are generated based on information from national databases such as construction year, building type and registered energy efficiency measures. In France preliminary EPC ratings are based on administrative records.

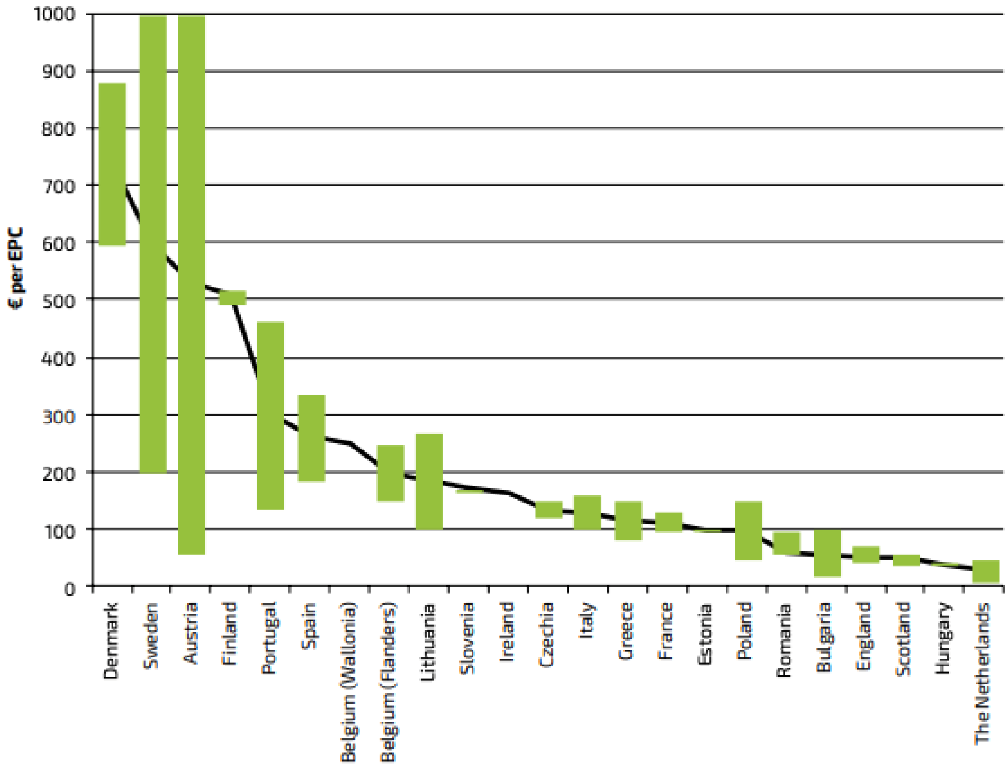

Figure 5 Cost range for an EPC for a single-family house. Original data sources: X-tendo partner provided information[26]

See, "Making SAP and RdSAP 11 Fit for Net Zero" a report for DESNZ June 2021, for a review of international ratings and calculation methods.

Causes of the gap

Many causes of the gap have been hypothesised; this section reviews some of the evidence under four categories:

- Measurement error
- Core calculation simplifications
- Inputs and assumptions
- The EPC process incentivising bias.

Measurement error

All measurements have an uncertainty, and measurements can result in systematic errors including in energy metering. For example, measurements of gas energy used in homes require the volume of gas used to be measured and this is converted to energy use using the calorific value. The calorific value is dependent on the temperature of the gas at the meter,

[26] Building Performance Institute Europe(BPIE), X-tendo report, Energy Performance Certificates: Assessing their status and potential, March 2020.

which is not typically measured so an estimation is used, introducing uncertainty into the energy use value. Systematic errors in the measurement of floor area are also possible if different conventions for measurement (such as measuring to the inside or outside of walls) are used or errors are made in the number of floors. This report investigates some of the measurement errors in meter readings and floor areas.

As part of our current research, we have been able to compare the difference between EPC Assessors and NEED in terms of the recorded age of a property and the number of storeys. Note that EPC age bands and NEED age bands do not align and so we have matched any overlapping bands (i.e. the matching is as generous as possible). Figure 6 suggests that there is uncertainty in both these key variables in the EPC registry and NEED. Note that it is not possible to determine which of these data sources is correct for any given building without individual investigation.

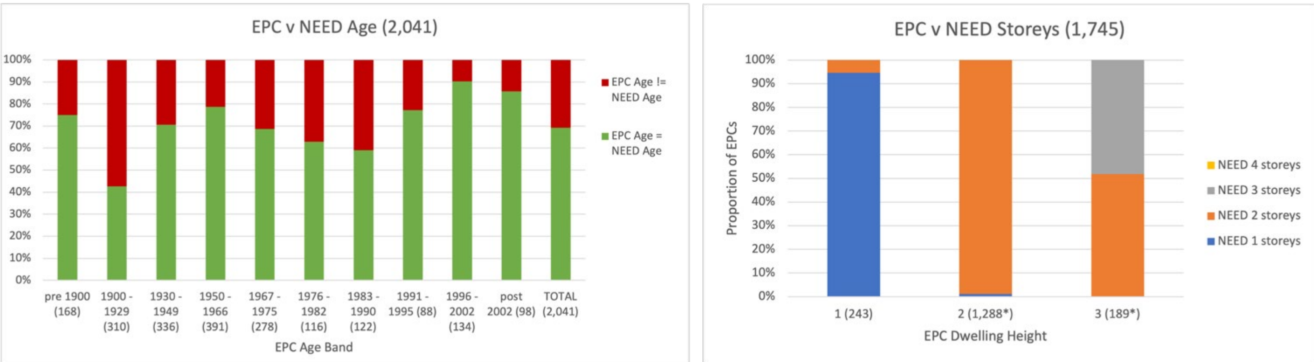

Figure 6 Left hand graph shows in red the percentage of homes where the EPC age does not agree with the NEED predicted age for each EPC generated age band (numbers in brackets are sample size). The right-hand graph shows for each NEED storey, the proportion of homes that have the NEED measured storey number. *There were <10 4-storey buildings and these have been removed from the bars for statistical disclosure control.

Core Calculation Simplifications

Mean Internal Temperature (MIT)

SAP uses a simplified calculation to determine the MIT in two zones of the building. It assumes an instantaneous warming of the building when space heat is required followed by a simplified cooling curve, plus it ignores residual heat in the heating circuit transferred to the dwelling outside the heating period. Fully transient models indicate that there is a significant gap between the mean internal temperature predicted by SAP and that of the dynamic cases; between 0.6ºC and 1.2ºC for a typically sized heating system[27].

[27] Bennett, G; Elwell, C; Lowe, R; Oreszczyn, T; (2016) The Importance of Heating System Transient Response in Domestic Energy Labelling. *Buildings* , 6 (3) , Article 29. 10.3390/buildings6030029

Assumptions

Occupant behaviour

Empirical evidence shows that there is considerable variation in occupant behaviour in identical homes over the same heating seasons which has been attributed to occupant variations in behaviour[28] . To characterise the distribution of variation in occupant behaviour requires sample sizes of at least 30 or so identical homes[29] to identify significant (20%) changes in energy saving technologies with any statistical confidence. This means that any research into differences in energy use associated with say 10 different characteristics of a building requires sample sizes of several hundreds and ideally thousands. The SERL and NEED data sets are unique in providing such large sample sizes, and in the case of SERL having monthly data plus much of the critical contextual data that is required to help unpick the impact of occupant behaviour.

SAP makes many assumptions, one of the most significant is the number of occupants in a house and how they behave. Uncertainty in these assumptions are often the focus when hypothesising the cause of a performance gap. There are differences in real and modelled occupant behaviour, particularly with regard to heating set-point temperatures, schedules, and whether the whole home is heated (e.g. Kelly et al., 2012[30]; Sunikka-Blank and Galvin, 2012[31]; Summerfield et al., 2019; van Hove et al., 2022). This is sometimes termed the rebound and pre-bound effect (Sunikka-Blank and Galvin, 2012). The rebound effect can refer to the phenomenon of increased internal temperatures following an energy efficiency retrofit, but is also used when referring to the suggestion that occupants in high-efficiency homes alter their space heating behaviour to provide higher internal temperatures than they would if they lived in a lower-efficiency home (even where a retrofit has not taken place). The pre-bound effect is the opposite whereby occupants seek lower temperatures, or heat fewer rooms, in lower-efficiency homes compared to higher-efficiency homes. It's important to realise that rebound effects may change over time as a result of cultural changes or rises in fuel prices. If a home is insulated an occupant may increase their demand temperature and so energy consumption can go up, but if fuel prices rise the occupants may take the benefit not as increased comfort but reduced energy use.

[28] Chapman, J, Lowe, R. and Everett, The Pennyland Project, Energy Research Group, Open University, ERG053, ETSU-S-1046, 1985. https://oro.open.ac.uk/19860/.
[29] "it is necessary to have groups of at least 30 houses to be 95% certain that an observed difference in energy use of about 2250 kWh/yr is a real difference and not simply an artefact of the statistical variation in energy use from one house to another" source Pennylands see footnote 19
[30] Kelly, S., Crawford-Brown, D. and Pollitt, M. G. (2012) 'Building performance evaluation and certification in the UK: Is SAP fit for purpose?', *Renewable and Sustainable Energy Reviews*, 16(9), pp. 6861–6878. doi: 10.1016/j.rser.2012.07.018.
[31] Sunikka-Blank, M. and Galvin, R. (2012) 'Introducing the prebound effect: The gap between performance and actual energy consumption', *Building Research and Information*, 40(3), pp. 260–273. doi: 10.1080/09613218.2012.690952.

Analysis of the EFUS energy data[32] has used the concept of a household "underspending" when its actual fuel expenditure is below that predicted by this theoretical regime. Figure 7 shows similar results to other studies highlighting the performance gap with poorly insulated homes using significantly less energy than SAP predicted and well insulated homes using more energy. Applying the label of 'underspend' implies that the gap is due to the behaviour of households rather than other potential causes. However, no relationship was identified between underspending and income, whereas a relationship between SAP rating and the performance gap was identified. Homes with the greatest underspend also had lower MIT, however this is to be expected as SAP predicts lower MIT in as poorly insulated homes, this is because they cool down more quickly.

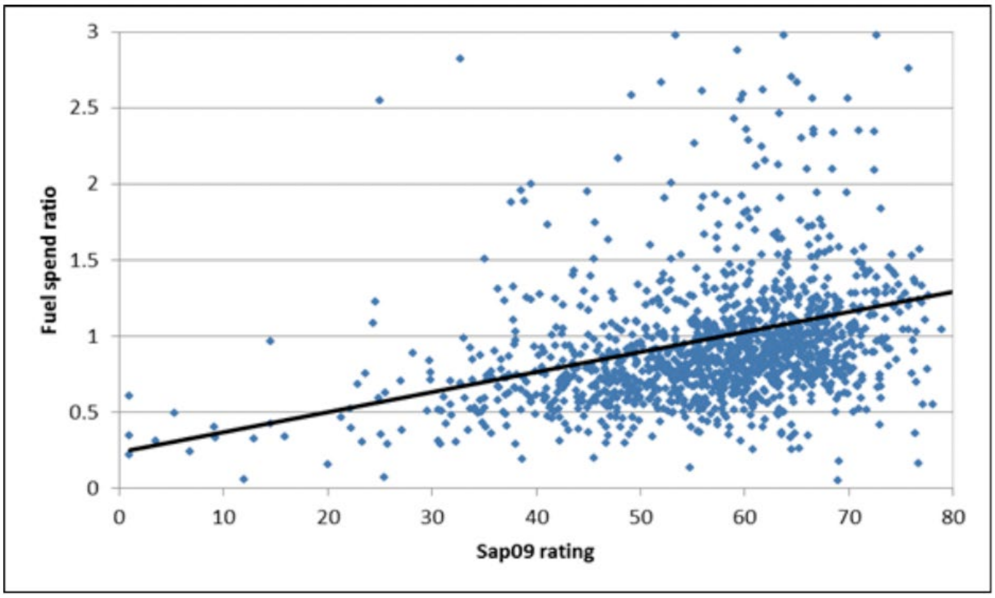

Figure 7 Relationship between SAP rating and fuel spend ratio (above 1 represents actual spend is greater than modelled, and below 1 less). Source: analysis of EFUS data, Hulme (2015)

Assumed Heat Loss

Typically, an RdSAP assessment makes many assumptions driven by the age of a property, unless there is documented evidence to overturn these assumptions. The assumptions are based on the age of the building and are derived from typical practices at the time of the construction. Many older homes will have had significant improvements since they were constructed and so the assumed U-values and ventilation rates may be conservative. In 2015 it was discovered that the assumed solid wall U-value of 2.1 W/m²K was incorrect (Li et al., 2016[33]), and consequently RdSAP-9.93 changed the defaults for several types of building fabric, these have again been changed in RdSAP-10, see Appendix I.

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[32] Jack Hulme " Energy use and home temperatures in English housing: results from the energy follow-up survey, ECEEE SUMMER STUDY PROCEEDINGS- First Fuel Now, 2015 p 1057- 1066, and EFUS2011 Report 10: Household underspend December 2013, BRE Report No. 288142

[33] Li, F. G. N. et al. (2015) 'Solid-wall U -values: Heat flux measurements compared with standard assumptions', Building Research and Information, 43(2), pp. 238–252. doi: 10.1080/09613218.2014.967977.

Several studies using co-heating tests and heat flux plates have indicated that EPCs do not predict building heat loss accurately. The evidence suggests that in general, uninsulated homes are not as poorly insulated as SAP predicts and new well insulated properties do not perform as well as SAP predicts. For example, one of the earliest comprehensive studies of SAP predicted heat loss versus measured was as part of a Carbon Trust micro-CHP field trial[34] where the heat emitted into a large number of homes was metered, along with measurements of the internal and external temperature, see Figure 8. This suggested that many poorly insulated homes lost 25% less heat than SAP predicted. Note, very similar results have more recently been reported by commercial companies using the SMETER (Smart Meter Enabled Thermal Efficiency Rating) technique such as by Building Test Solutions[35]. It is possible to hypothesise an explanation for this trend: in uninsulated properties poor construction can lead to pockets of air trapped improving the performance of the fabric while in homes with lots of insulation poor construction can lead to air movement around the insulation and thermal bypasses.

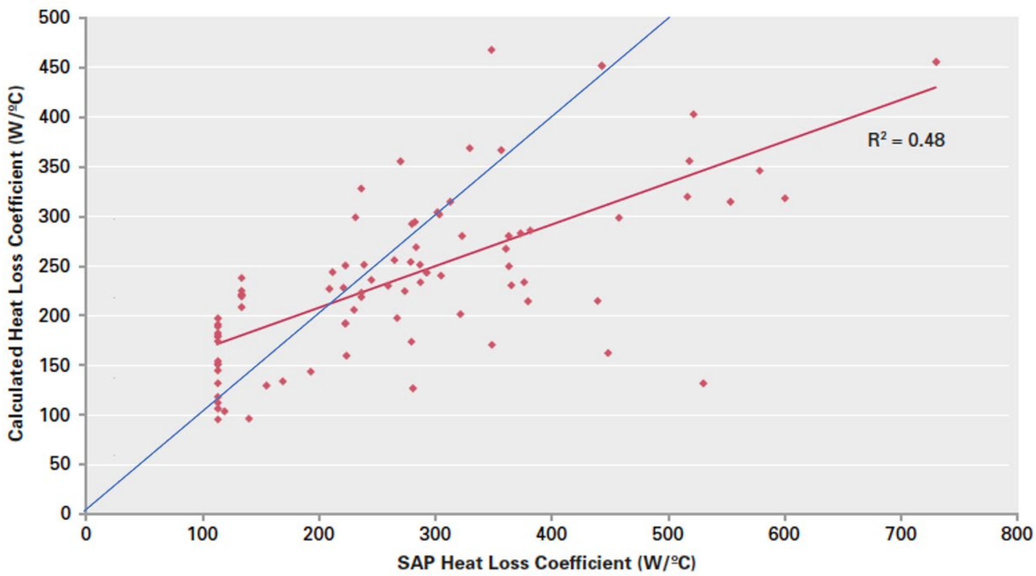


Figure 8 Calculated heat loss coefficient from metered heat input into the building versus SAP modelled heat loss for a range of different heating systems. Each point is a single house. Red line is best fit, blue line, one to one, i.e. all data would lie on this if SAP modelled data predicted measured data. Homes with high heat loss are better preforming than modelled and well insulated homes do not perform as well as expected. Source: Carbon Trust, Micro CHP Accelerator Interim report, 2007.

The ventilation rate assumptions have been known to have had the least empirical verification because of the complexity of measuring in-situ ventilation rates in occupied properties. SAP has an effective minimum ventilation rate of 0.5 ach for naturally ventilated properties to comply with Building Regulations Approved Document F[36]. In practice properties may have a very diverse range of ventilation rates. It is possible that on average ventilation rates have

[34] Carbon Trust, Micro-CHP Accelerator, Interim Report November 2007.
[35] Private communication from Richard Jack, Build to Perform 2024
[36] HMG (2013) Approved Document F1: Means of ventilation. 2021. Her Majesty's Government.

reduced over time as buildings have been increasingly sealed due to better fitting windows, doors with integrated draught stripping, fewer open fire places, more sealed balanced flues and increased prevalence of fitted carpets and engineered flooring with thick noise absorbing underlay. In homes with a high level of fabric insulation ventilation heat losses are responsible for a high proportion of the overall heat loss, so these assumptions are particularly important in well-insulated buildings.

While there is very limited empirical evidence, some recent research finds ventilation rates far lower than the minimum modelled by SAP. Van Rooyen (2024)[37] conducted extensive longitudinal research on 7 case study dwellings (6 out of 7 case studies were monitored for over 250 days), showing that when all windows were closed, median air change rates were closer to 0.25 ach than 0.5 ach for 6 out of the 7 case study dwellings. During occupied times in winter, median measured air change rates ranged from 0.23 ach to 0.46 ach.

EPC process and assessors

Interviews with EPC assessors suggest that they may be 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. For example, the following quotes from EPC assessors taken from Gledhill (2022)[38] on EPC assessments and their variability:

> *"There is pressure for DEAs [Domestic Energy Assessors], especially if they're self-employed, to actually lean towards what they've been told (to do) to get their money";*
> *"always look to give it a lower score if possible (the RdSAP defaults), so if you're not sure whether the windows were pre-or post-2002 if you can't find a date stamp you're (supposed, according to the Conventions) to say pre-2002 which will reduce the score and the effect that has is that if you're looking to lower the score to uplift the carbon savings, you're actually being encouraged to do that in a way by the Conventions or the rules of the EPC. So they were there (originally) to stop people enhancing scores (to make a property for sale or rental look more attractive) but now they're being used in the energy efficiency measure process it's having the opposite effect really, people are using it to downgrade the score where possible.";*
> *"The downside of (RdSAP) EPCs is that it's assuming too much. The on-construction EPCs don't assume anything, do they, but with RdSAP it's assuming too much. I think we should investigate things more. We're getting incorrect recommendations because it's not an intrusive survey".*

Shortcomings or inaccuracies in the quality of the input data

Increasing modelling accuracy is often associated with more model inputs, which in turn can result in assessors collecting more data. Historic analysis suggested an error rate of 5 errors per 100 data items for trained professional users. It is this error rate that becomes the overall

[37] Van Rooyen (2024), The relationship between ventilation practices and indoor environmental quality in British homes. (Thesis). University College London.
[38] Gledhill (2022) A study into the variability of UK domestic energy assessments. (Thesis). University of Salford.

limiting factor in the overall reliability of models unless methods are adopted to minimise this assessor error. [39]

Several authors note that the practical implementation of the building performance assessment is undertaken by assessors who are trained to make use of default input values for model parameters. The default values are pessimistic by design, with the intention that the resulting output does not indicate a better-than-merited rating, highlights the advantage of carrying out a retrofit, encourages the identification of accurate information for an accurate rating and encourages the recording of energy efficiency upgrades (Cozza et al., 2020[40]; Raushan et al. 2022[41]). Raushan et al. (2022) explored the Irish EPC record and found that default U-values for elements such as walls and floors were almost always higher (suggesting worse insulating performance) than those recorded when more information was available to conduct a tailored U-value estimation. Although the assessors may be performing the assessment in accordance with guidance, the use of pessimistic default values could have the effect of increasing the modelled consumption compared to the real value. A separate issue related to the practical implementation by assessors was noted by Jenkins et al. (2017)[42] and Crawley et al. (2019)[43], who both found large uncertainties in the EPC rating, showing that when the same dwelling is rated repeatedly the resulting rating changes considerably.

The energy intensity of homes in the UK has seen a general trend of reducing over the last 25 years as shown in Figure 9 below[44], mostly due to energy efficiency. This makes comparing data from historic EPCs challenging. Many homes will have been significantly improved since their last EPC. Note, over the last five years energy use has increased and then reduced likely due to changes in behaviour associated with COVID lockdowns, increased working from home and very significant changes in domestic fuel prices.

[39] Chaman, J. Data Accuracy and Model Reliability, BEPAC Canterbury Conference, 1991, p10-19
[40] Cozza, S. et al. (2020) 'Do energy performance certificates allow reliable predictions of actual energy consumption and savings? Learning from the Swiss national database', Energy and Buildings, 224, p. 110235. doi: 10.1016/j.enbuild.2020.110235.
[41] Raushan, K., Ahern, C. and Norton, B. (2022) 'Determining realistic U-values to substitute default U-values in EPC database to make more representative; a case-study in Ireland', Energy and Buildings, 274, p. 112358. doi: 10.1016/j.enbuild.2022.112358.
[42] Jenkins, D., Simpson, S. and Peacock, A. (2017) 'Investigating the consistency and quality of EPC ratings and assessments', Energy, 138, pp. 480–489. doi: 10.1016/j.energy.2017.07.105.
[43] Crawley, J. et al. (2019) 'Quantifying the Measurement Error on England and Wales EPC Ratings', Energies, 12(3523). doi: 10.3390/en12183523.
[44] DESNZ (2024) Energy Consumption in the UK (ECUK) 1970 to 2023.

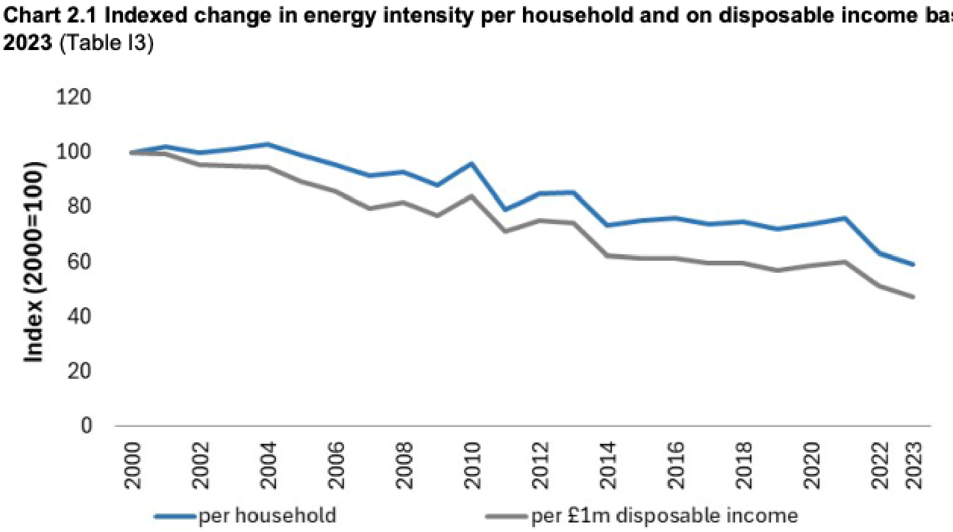


Figure 9 Indexed change in energy intensity per household and on a disposable income basis, 2000 to 2023. Source: DESNZ (2024) Energy Consumption in the UK (ECUK) 1970 to 2023

No Gap, No Problem?

There have been many previous studies exploring the gap between metered and SAP-modelled energy use. If no gap occurs it is possible to assume that the model is performing well. On the other hand, where a difference has been observed, this has often been attributed to a singular cause. For example, (BRE EFUS) suggest that the discrepancy is largely associated with differences between the way real occupants use their homes and the normative assumptions made in SAP. Similarly, previous versions of the model have been adjusted or calibrated to match national average residential energy data by adjusting typically one variable – the mean internal temperature. While these approaches may be convenient and relatively simply allow the average actual energy use to match the average modelled energy use, it also masks the diversity in energy use in domestic properties. Indeed, modelling the diversity of domestic energy uses is one of the primary purposes of the EPC processes, with the aim that different buildings can be straightforwardly compared in terms of their energy efficiency, or to show the value and benefit of improving an inefficient house.

We anticipate that there are many causes of the observed gap, given the complexity and nuance of building energy modelled and measurement in occupied homes. We have tried to avoid a narrow interpretation of the results of this analysis, and developed our analysis plan with reference to the factors considered important in the literature prior to carrying out the analysis, and in collaboration with DESNZ. Given the unique combination of data streams we had access to for this project, including detailed EPC input data, household level smart meter data, and internal temperature data, we were able to explore a good breadth of factors likely to be related to the performance gap.

Model Validation

It is infeasible to fully validate a building energy model for several complex reasons:

1. Energy use in a buildings is socio-technical and modelling occupants and their energy use is challenging without extremely intensive monitoring.
2. The number of variables that impact a buildings energy use significantly, by more than 10%, are probably in the 10's, but EPCs aim to model buildings in greater detail than this to model smaller changes (for example to encourage energy efficiency adoption) and this results in 100's if not 1000's of relevant variables. The number of variables that assessors now collect has significantly increased. The new HEM model may see this increase significantly. Measuring all these variables to an appropriate level of accuracy is challenging.
3. Control of variables – this is normally the reductionist method of validating theoretical science models whereby as many conditions are controlled as possible. This kind of process typically takes place in highly controlled laboratory environments. Although laboratories are useful for controlling some variables, the physical size and complexity of controlling all variables accurately for a house, including radiant heat loss, wind-driven and stack-driven ventilation and solar gains accurately (not no mention occupant behaviour) would require much more resource than is currently expended in this area.
4. Many aspects of a building's structure can significantly impact its energy efficiency, but these are hidden once the building is complete, for example thermal bridging detailing cannot easily be observed non-destructively. This means that controlling for construction quality post-build is extremely challenging.
5. Collecting all the types of data noted above in a sample of sufficient size is challenging.

However, it is possible to recognise the limitations and nonetheless gain confidence in the use of models and whether they typically accurately replicate the key outcomes that the model has been designed to predict.

Data sources

SERL

This analysis in this report uses the SERL Observatory which contains seven datasets linked at the household level: electricity smart meter data, gas smart meter data, tariff data, weather data[45], location data, participant survey data and EPC data, see Figure 10 (for full details see

[45] The SERL Observatory includes European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 data. Neither the European Commission nor the European Centre for Medium-Range Weather Forecasts is responsible for any use that may be made of the Copernicus information or data it contains.

Webborn et al., 2021[46]). The SERL Observatory has 13,000 participants and is approximately representative of GB dwellings by region and index of multiple deprivation (IMD) quintile. Just over half of the SERL participants have an EPC. Analysis for this project used SERL Observatory Edition 6[47].

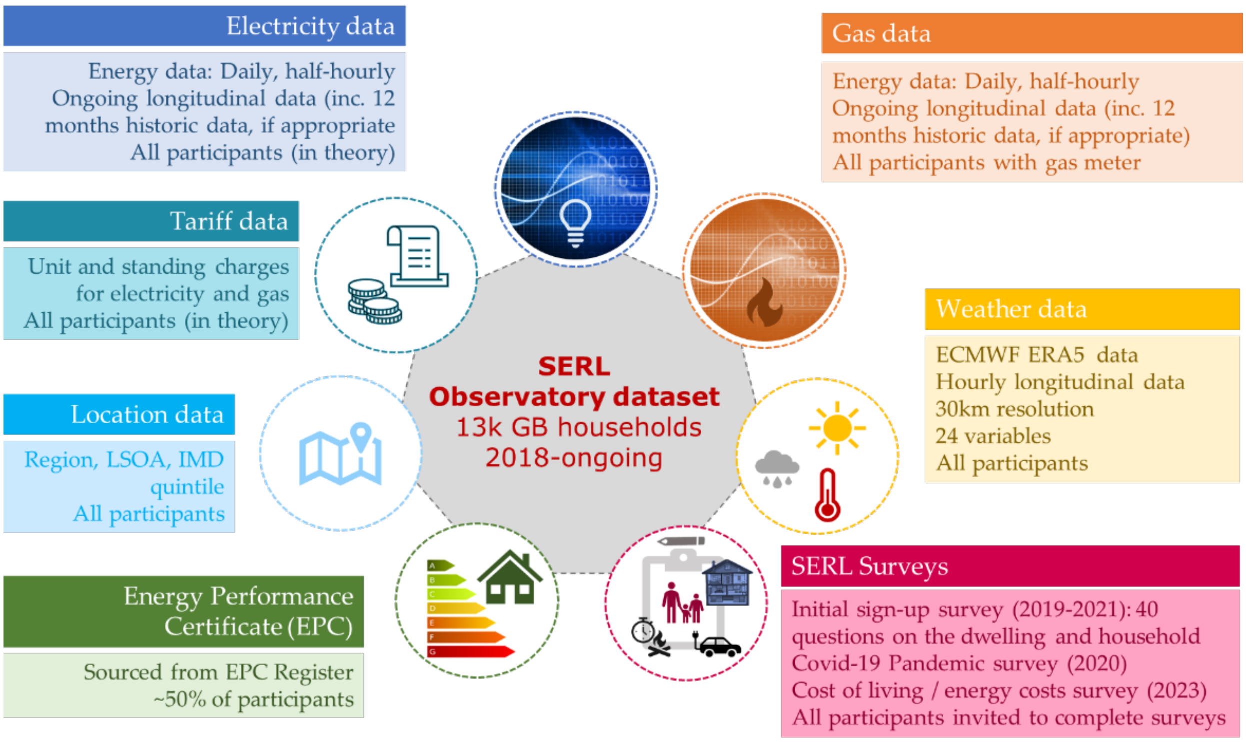


Figure 10 Schematic summary of data collected as part of the Smart Energy Research Lab Observatory

The following filtering is applied to the SERL Observatory database to enable the metered data to most closely replicate the modelled scenario:

1. Homes with an EPC available through the SERL Observatory
2. Homes with a recorded floor area between 20 m² and 500 m², which are self-contained according to the SERL survey
3. Homes with sufficient energy data quality - at least 50% of gas and electricity readings available in each month (see 'implementing the energy signature method' section below for further information on energy data requirements including the filtering used to remove days where the home is potentially unoccupied)
4. Homes with mains gas central heating, based on SERL survey responses regarding the main heating system. Comparing homes with the same heating type means that the energy uses associated with each energy vector are similar, increasing the reliability of the comparison.

[46] Webborn, E. et al. (2021) 'The SERL observatory dataset: Longitudinal smart meter electricity and gas data, survey, EPC and climate data for over 13,000 households in Great Britain', Energies, 14(21). doi: 10.3390/en14216934.

[47] Elam, S., Few, J., McKenna, E., Hanmer, C., Pullinger, M., Zapata-Webborn, E., Oreszczyn, T., Anderson, B., Department for Levelling Up, Housing and Communities, European Centre for Medium-Range Weather Forecasts, Royal Mail Group Limited. (2024). Smart Energy Research Lab Observatory Data, 2019-2024: Secure Access. [data collection]. 8th Edition. UK Data Service. SN: 8666, DOI: http://doi.org/10.5255/UKDA-SN-8666-8

5. Homes where the EPC and SERL survey agree over the main heating fuel in the home. Some homeowners reported different heating systems to that reported by an EPC assessor and this would result in differences in each energy vector.
6. Homes where any secondary heating was either mains gas or electricity (i.e. the energy use was metered)
7. Homes without an electric vehicle (EV) according to the SERL survey. Excluding EVs avoids the metered data including electricity use for charging the car which is not included in the SAP model so would lead to a discrepancy.
8. Homes without photovoltaic (PV) electricity generation. There are discrepancies between the way the SAP model treats electricity generation and the way smart meters record electricity consumption so homes with PV are excluded for clarity in interpreting the results.
9. Homes in England and Wales only, because the Scottish EPC system is slightly different

These filters resulted in a final subset of 2,134 homes from the SERL observatory which could be used for this analysis. However, not all of these homes could be modelled using NBM for a variety of reasons (see the EPC input section below, and the filtering applied to the energy signature analysis). The final sample of homes used for the metered to modelling comparison was 674. It would be possible to expand the sample size by relaxing the inclusion requirements. However, for this analysis it was desirable to make the comparison between the metered and modelled data as fair as possible to increase confidence that differences were genuine effects rather than artefacts of the types of homes included in the analysis.

EPC input

MHCLG holds a record of the assessor data used to create each EPC in England and Wales, i.e. the data exported from a SAP or RdSAP EPC calculation that is used for the core calculation. Note, each commercial SAP software uses different assessor input files that are used to derive the core calculation input data to SAP. This database was queried using the UPRN (Unique Property Reference Number) to obtain the EPC input data for SERL Observatory homes.

EPC registry

The Energy Performance of Buildings Directory (https://epc.opendatacommunities.org/) makes some data from EPCs lodged since 1st October 2008 available for research purposes. EPCs are excluded from the register if the holder of the certificate has opted out of disclosure or if the certificate is marked as 'cancelled' or 'not for issue'. The database contains approximately 25 million records. Some homes have multiple EPCs while others have none recorded in the database. The SERL Observatory links to the most recent EPC available in this dataset for SERL homes, approximately half the SERL Observatory homes have an EPC. For this report we make use of the full EPC directory and identify cases where the same home (as identified by its UPRN) has multiple EPCs lodged in the register to investigate changes over time. Note that the EPC registry makes available the outcomes of the EPC assessment, but not the parameters used to generate the rating (e.g. the SAP score and wall description are provided, but the wall U-value and delivered energy requirements are not).

NEED

The National Energy Efficiency Data-Framework (NEED) is a property level dataset which links together a number of datasets, including both annualised energy meter consumption data, and energy efficiency improvement data. For example, if a home has had cavity wall insulation installed under a government scheme such as the Energy Company Obligation (ECO), the date the measure was installed and type of improvement are included in NEED. NEED data can therefore be used to help identify if a home has been upgraded since its EPC was lodged. This can help identify homes where a performance gap might reflect the changes to the building, rather than a calculation error.

EFUS temperature data

As part of the English Housing Survey (EHS) a sub-sample of properties undergo more detailed monitoring and surveying approximately every 5-years, this is known as the Energy Follow-Up Survey (EFUS). The last EHS survey was begun in 2017 when the first round of interviews took place. A second and third round of interviews took place in 2018 and 2019. Temperature monitoring took place from October 2017 to the end of April 2019.

Temperature was monitored in up to 5 rooms including the Living Room, Hall, and Bedrooms 1 to 3 depending on the layout of the dwelling using Tinytag Transit 2 temperature loggers with an accuracy of +/-0.4°C. These loggers were programmed to record temperatures at 30-minute intervals and to continue logging until the memory was full. Of an initial 3853 loggers sent to participants, a total of 2580 loggers corresponding to 750 individual dwellings were returned and found to be suitable for analysis following cleaning by the EFUS survey team. Details of this cleaning procedure and the installation process can be found in the Energy Follow Up Survey 2017 Methodology report[48].

External hourly temperature data was gathered by the EFUS team from the Met Office MIDAS-Open archive, and each dwelling was paired to its nearest weather station, resulting in 150 weather stations paired with 750 homes. This data was also cleaned by the EFUS team to remove duplicate readings (see EFUS Methodology report). Further information about this data is available on the CEDA Archive.

Further to the cleaning performed by the EFUS team, the indoor and external temperature data was cleaned to suit the purposes required for this analysis.

[48] BEIS (2021) *Energy Follow Up Survey 2017: Methodology report*. Department for Buisiness, Energy and Industrial Strategy.

Note, the EPC’s used as part of the EFUS temperature analysis are not EPCs generated by a normal EPC Assessor and registered in the EPC Registry. The EPCs and SAP ratings for EFUS homes is based on data collected by EHS surveyors and may use slightly different conventions for the SAP calculations. Since the survey was done at a similar time to the temperature monitoring the EPC should be up to date with any change that have taken place in the home and so probably closer to what is called a scenario 3 SAP calculation later in this report.

To test the validity of the results generated using EFUS temperature data, GHG temperature data was also used, see Appendix F.

Methods – Part 1 Gas Heated Homes

This section explains how the various data sources have been linked, filtered and analysed to help answer the research questions.

NBM-SERL

For policy development government has developed a model of the stock of UK buildings, called the National Buildings Model (NBM); historically the domestic stock model was called the National Housing Model (NHM). This includes a stock-level implementation of SAP, which can generate EPC data for thousands of buildings. NBM normally runs with English Housing Survey (EHS) building stock data but for this project it models SERL Observatory homes analysed for this report, we call this NBM-SERL. This allows a detailed comparison of the SAP model (run under different scenarios including different RdSAP vintages, weather, occupancy and appliance algorithms) with smart meter data from the SERL Observatory homes, Figure 11 presents a schematic of the process.

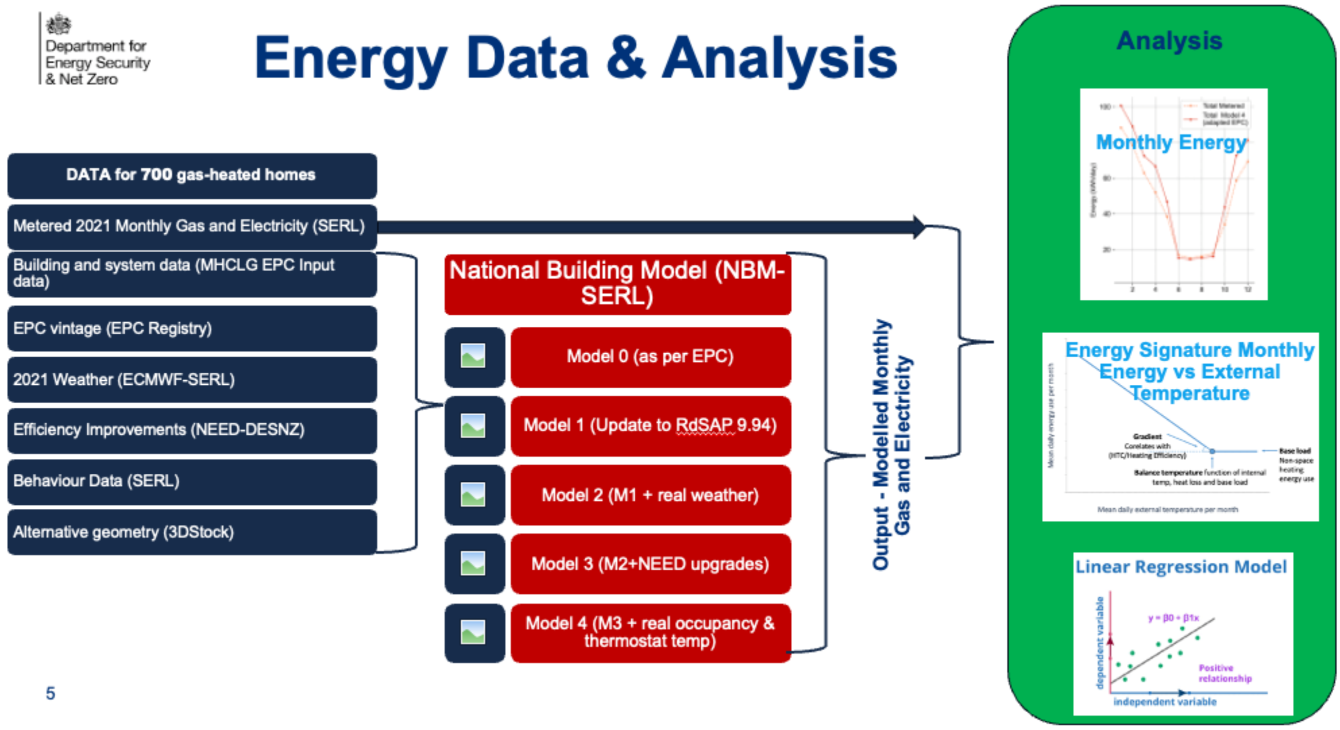


Figure 11 Schematic of data analysis and scenarios modelled to compare monthly modelled energy use against metered energy use.

A detailed SAP-2012 model of each SERL Observatory home has been constructed so that monthly modelled gas and electricity consumption can be compared with SERL metered data. A base case was modelled with NBM-SERL that replicated the EPC Assessor SAP calculation, see Appendix D.

Scenarios have been modelled using self-reported occupancy from SERL, as well the default SAP assumptions, to better understand modelling uncertainties. Other data sources have also been linked such as NEED (the domestic National Energy Efficiency Data-Framework) and EPC input data from MHCLG, to further help identify additional uncertainties, by cross-checking the accuracy of EPC input data.

For each of the SERL Observatory homes that have been filtered, a SAP2012 input file is generated from EPC Input, and NEED energy efficiency data.

SERL holds weather data for each participant from the Copernicus ERA5 hourly reanalysis data[49] (this is a modelled weather data created from measured weather station data reported on a 30km square grid which is then linked to homes in that grid square). This has been used to generate a monthly SAP-2012 compatible weather file for each home, for the year that the

[49] Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J-N. (2023): ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), DOI: 10.24381/cds.adbb2d47

meter data is compared, 2021. This is used to replace the climate files normally used by SAP in some of the scenarios modelled (Scenarios 2 to 4).

NBM-SERL generates a monthly file of gas and electricity use for each of the filtered SERL Observatory sample. It should be noted that the electricity use includes appliance and cooking energy uses even though these are excluded from a normal EPC calculation as these energy uses are not ‘regulated’. By including these energy uses we make the modelled and metered energy use as comparable as possible. In addition, for each month; the hot water, space heating, cooking, lights, and appliance energy use is generated for comparison with the SERL metered data. NBM-SERL also calculated the predicted Mean Internal Temperature (MIT) for each home, for each month for use in temperature analysis. This modelling is repeated using different defaults that correspond with different vintages of RdSAP.

Despite having access to the SAP input data for this project there were some ambiguities when transforming the input files into SAP models via NBM, for example associated with rounding errors. The vast majority of the SAP models generated via NBM showed very good agreement with the commercial SAP assessment, 91% agreed within one SAP point. A small number disagreed by more than 2 SAP points, and these were filtered out of subsequent analysis, see Appendix E.

The following scenarios are modelled with NBM-SERL to help identify the causes of any performance gap, with the hypothesis that the gap is reduced as the model is run with more realistic input data:

- Scenario 0: the base-case with EPC inputs and EPC model assumptions reflecting the version of SAP used to generate the lodged EPC, this replicates the SAP as registered in the EPC Registry as closely as possible.
- Scenario 1: all homes modelled using RdSAP 9.94. This version of RdSAP made several important changes to assumptions (particularly around solid wall U-values)
- Scenario 2: scenario 1 + actual regional weather for the year of analysis instead of SAP assumed weather.
- Scenario 3: scenario 2 + any home energy efficiency measures recorded in NEED between EPC lodgement and the year of analysis included in the model.
- Scenario 4: scenario 3 + actual number of occupants according to participant survey used instead of SAP assumed number of occupants based on floor area, and demand temperature changed to match participant-reported thermostat set-point instead of SAP assumed 21°C.

Table 3 summarises some of the key characteristics of the group of 674 homes used for the metered to modelled comparison, showing a spread across property characteristics and built forms. Table 4 gives the mean values of some of the key modelled parameters for these homes by EPC band for scenario 0 (EPC as-found). Note that there are very few F&G and A&B homes in the analysis. There are relatively few homes at the extremes of energy efficiency in the building stock so it would be expected that there would be an uneven distribution of homes throughout the bands. Moreover, this analysis has explicitly removed the types of homes likely to be A&B by filtering out those homes with solar PV. Homes likely to be F&G are also likely to be excluded as these homes are much more likely to have non-gas heating as this is more expensive and therefore drives the ratings towards the poorer end. This means that the results at the extremes should be interpreted cautiously, and we have included standard errors in our results to aid in this interpretation.

Table 3 Dwelling characteristics of the 674 homes used for modelled to metered comparison

EPC band	N	Dwelling age	N	Wall type	N	Property type	N	Built form	N
A & B	3	Pre-1900	35	Cavity wall, as built, insulated (assumed)	127	House	496	Semi-detached	250
C	243	1900-1929	102	Cavity wall, as built, no insulation (assumed)	98	Bungalow	91	Mid-terrace	179
D	355	1930-1949	111	Cavity wall, filled cavity	235	Flat	80	Detached	164
E	66	1950-1966	119	Solid brick, as built, no insulation (assumed)	154	Maisonette	7	End-terrace	78
F & G	7	1967-1975	91	Other	60				
		1976-1990	95						
		1991-2002	81						
		2003 onwards	39						

Table 4 gives the mean values of some of the key modelled parameters for these homes by EPC band for scenario 0 (EPC as-found). As expected the average modelled U-values and ventilation rates for building components increase from bands C to F and G, while the internal temperature decreases. Homes in band C are on average notably smaller than other bands, and homes in F and G are larger.

Table 4 Mean modelled values of building parameters for homes in different EPC bands used in the NBM-SERL analysis under scenario 0 (EPC as-found).

Parameter	C	D	E	F and G
Mean wall U-value (W/m²K)	0.61	1.08	1.59	1.91
Mean roof U-value (W/m²K)	0.27	0.59	1.35	1.82
Mean exposed floor U-value (W/m²K)	0.73	1.00	1.20	1.20
Mean ground contact floor U-value (W/m²K)	0.54	0.63	0.66	0.70
Mean dwelling floor area (m²)	85.8	93.1	97.6	134.0
Mean heating season air change rate (ach)	0.66	0.70	0.73	0.87
Mean heating season heat loss parameter (W/m²K)	2.32	3.30	4.45	5.16
Mean heating season heat transfer coefficient (W/K)	198	303	432	672
Mean overall adjusted mean internal temperature (°C)	18.8	18.1	17.6	17.2

Table 5 shows the energy efficiency interventions lodged in NEED and modelled for scenario 3. This shows that by far the most common intervention is for the heating and hot water system efficiency to be improved. Only 48 homes were recorded as having a fabric efficiency improvement between their initial EPC and the year of comparison – 2021. Not all efficiency measures would be lodged in the NEED data, in particular there are few window replacements lodged in the data although there are likely to have been many in the period of interest.

Table 5 Summary of energy efficiency measures recorded in NEED for the 674 homes in the metered-modelled energy comparison.

Measure	Count
No hot water system change - combi throughout	452
No hot water system change - system throughout	120
Hot water system change - system to combi	102
Hot water efficiency upgraded	219
Hot water efficiency worsened	27
No hot water efficiency change	428
No wall change	647
Walls upgraded	27
No roof change	653
Roof insulation upgraded	21
Heating efficiency upgraded	237
Heating efficiency worsened	7
No heating efficiency change	430

The NEED data lacks detail on the specific boilers installed for each dwelling (it lists the 'measure_type' as 'Boiler'). The default gas boiler data in SAP (table 4b) shows low efficiencies. Since these are all recently installed boilers the data from PCDB for code 690102 was used, which is an instantaneous combi gas boiler for the building regulations notional dwelling. The SAP efficiency adjustments (e.g for different controls) were then applied as normal in scenario 3.

Energy signature

A common model used for analysing how energy use changes with external temperature is often referred to as 'energy signature' or 'power temperature gradient' analysis. The energy-signature method has been used for many applications, including underpinning the SMETER (Smart Meter Enabled Thermal Efficiency Ratings) techniques[50] Figure 12 provides a visualisation of the model, and the following equations describe the model mathematically:

$$E(T_{ext} \geq T_{bal}) = E_b$$

$$E(T_{ext} < T_{bal}) = E_b + m(T_{ext} - T_{bal})$$

Where *E* is the daily energy use, *Text* is the daily mean external temperature, *Tbal* is the balance temperature, *Eb* is the base energy use or base load, and *m* is the energy-

[50] https://www.gov.uk/government/publications/smart-meter-enabled-thermal-efficiency-ratings-smeter-technologies-project-technical-evaluation

temperature gradient. Note that this model can equivalently be generated using average power instead of average daily energy (as the two are interchangeable with a fixed multiplier), and at times in this report we may refer to either.

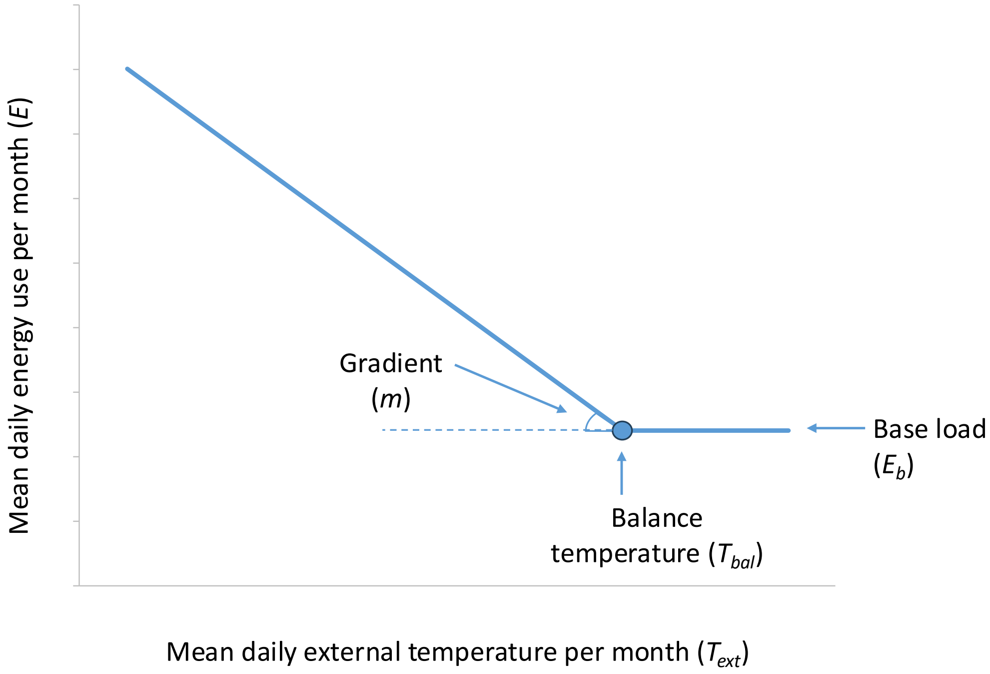


Figure 12. Schematic diagram of the energy signature model

The parameters of the model can be interpreted as having physical meaning in the following ways:

- The base energy use is associated with the summer energy use, when the daily energy use is not related to the external temperature.
- The balance temperature denotes the maximum external temperature for which heating is needed in the home. At temperatures colder than this space heating is needed and at higher external temperatures the indoor environment is kept warm enough from solar and internal gains. Historically, the balance temperature was assumed to be 15.5ºC, and this is the basis of the degree-days method of energy analysis. However, the balance temperature is variable for different homes, and can typically range between 10ºC to 17ºC
- The energy-temperature gradient is the amount of delivered energy required to raise the internal temperature by 1ºC, or equivalently to keep the home at the same temperature if the external temperature drops by 1ºC. In theory the value of this parameter, when expressed as a power temperature gradient, should be well described by the heat transfer coefficient (HTC) divided by the heating system efficiency, known as the Heating Power Loss Coefficient (HPLC).

The interpretation of the gradient as the HPLC was theoretically tested using modelled data by comparing the NBM modelled HTC/heating system efficiency with the gradient produced from the energy signature of the NBM modelled monthly energy use values, and was shown to have extremely good agreement as shown in Figure 13. In much of the following, we normalise the HPLC by floor area and refer to this as the HPLP – Heating Power Loss Parameter.

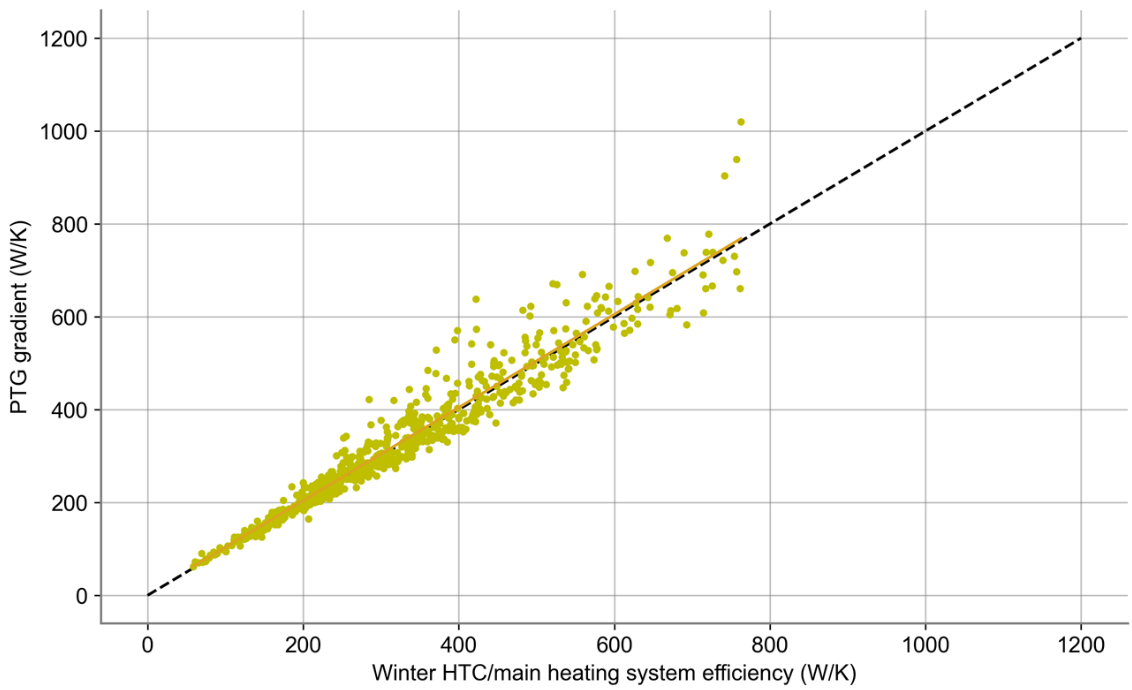


Figure 13 Agreement between the power temperature gradient fitted on the SAP modelled monthly energy use and the NBM/SAP modelled HTC/heating system efficiency, the best fit line has a gradient of 1.01 and the R^2 is 0.94. Note that both the x and y axis are based on modelled data.

In this report we compare the parameters derived from energy signature models fitted on monthly metered data and monthly modelled data generated by NBM. This comparison helps to identify the sources of the performance gap in response to research questions 1 and 2. If the gradient is similar for modelled and meter data then this suggests the modelled and monitored HTC/efficiency is similar; if the base load is similar for gas this implies appropriate modelling of hot water and if the electricity base load is similar this implies appropriate modelling of lights and appliances; and finally if all three parameters are similar this would imply similar mean internal temperatures (MIT).

We compare the energy signature for different groups of homes to draw out relevant areas where the model differs from the empirical evidence. Our analysis first compares the energy signature parameters for the full sample of homes included in our analysis for each of the NBM scenarios listed in the previous section. This helps to identify the overall impact of the measures implemented in each scenario. We then compare parameters from the metered energy data, the base case, and scenario 4 (RdSAP9.94, actual weather, NEED energy efficiency upgrades, and actual occupancy) for key subgroups of the sample, including:

- Wall type

- Building age
- Loft insulation level
- Main heating system efficiency
- Floor type
- Level of agreement over the number of occupants according to SAP and the participant survey
- Hot water system efficiency
- Type of hot water system – combi or system boiler.
- EPC transaction type (reason for EPC generation)

Implementing the energy signature method

To implement the energy signature method, we take several steps to make the metered energy data and NBM-SAP modelled energy data as comparable as possible. We also use this filtered metered energy data for the metered to modelled energy use comparison to ensure this is as similar to the SAP modelled energy use as possible. The SAP model assumes consistent heating throughout the heating season, and uniform use for other services throughout the year, which may not be the case in real homes (particularly because of holidays). If energy use on 'holiday days' was not removed it would tend to bias the metered energy towards lower values. To address this, we apply the following filters to the daily energy use before calculating monthly averages:

- We firstly remove any days where the sum of daily electricity and gas use is zero - this is likely erroneous.
- We then fit a preliminary energy signature model for each home using a least squares fitting algorithm (curve_fit from scipy).
- During the heating season (when Text<(Tbal-1.5C) from the preliminary model), we remove days when the total energy use is less than Eb. This suggests the heating is off during the heating season. We also remove the following day, since if the heating has been switched off then there would be greater energy use the next day to re-heat the building. This provides a better match to the SAP assumption that heating is used throughout the heating season.
- During the summer (when Text>Tbal), we identify large gaps in the distribution of total energy use, where the energy use is significantly lower than normal. We assume this is due to summer holidays, where energy use is considerably different to normal because of a lack of cooking, hot water and appliance use. This better matches the SAP assumption of no holidays.
- Finally, we remove days with an unrealistically high energy use given the floor area.

Figure 14 below illustrates the energy use data and the points that are filtered out for further analysis, and Table 6 shows the number of days that were removed for each of these reasons.

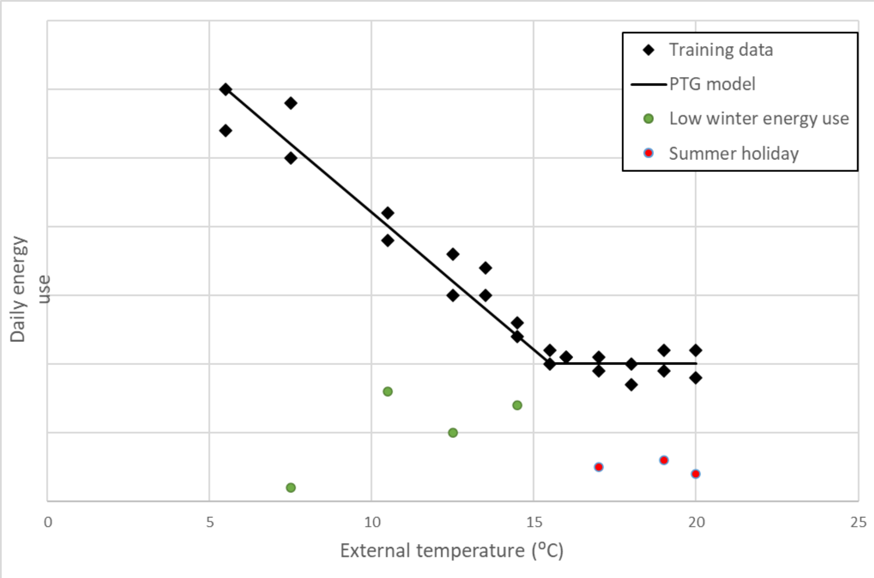


Figure 14 Schematic diagram of the types of daily energy use that are filtered out of the analysis.

Table 6 Summary of the days removed and number of homes affected by filtering of the energy data.

Filter	Mean days removed per home	Standard deviation of days removed per home	Number of homes affected
Winter low energy use	14.8	19.9	2175
Summer low energy use	8.6	16.6	1569
High energy use	0.3	2.5	106
Zero electricity	0.2	4.5	15
Base energy less than minimum daily energy use	N/A – these homes were removed completely	N/A – these homes were removed completely	2
PTG model could not solve	N/A – these homes were removed completely	N/A – these homes were removed completely	1

After the data has been filtered according to the above points, we aggregate the daily data to monthly values to match the frequency of the SAP model. For each month we require at least 50% data availability after filtering to give an average metered energy use for the month, and we require all 12 months to be available for the household to remain in the analysis. We use the monthly values to generate energy-signature models for the electricity, gas, and total energy use for both the metered and modelled cases and fit the model using a least squares algorithm. This analysis is repeated with different modelled scenarios.

We assess the fit of the models using indicators including R^2, mean absolute percentage error (MAPE) and the root mean square error (RMSE). Initial analysis of the parameters revealed that the distribution of the gradient was skewed, with a handful of very high values (>7.5 W/m²K) significantly affecting the mean. Further analysis showed that many of these cases had low balance temperatures (<10ºC). There are possible physical explanations for this: the house could have very high heat loss but be heated to a very low temperature, or it could have very high heat loss and very high internal heat gains and therefore be heated to a more normal temperature. However, many of these cases also showed poor model fits with high MAPE (>50%), investigation of the individual cases revealed that some winter heating months had erroneously been included in the summer base energy part of the model, as the winter energy use was inconsistent with external temperature. Cases with either HPLP >7.5 W/m²K or MAPE >50% were removed from further analysis.

Regression analysis

Linear regressions have often been used to investigate the factors influencing domestic energy consumption[51],[52]. Here we use regression analysis to investigate the factors influencing the difference between metered and modelled energy use for model scenario 0 (EPC as-found) using variables available via the EPC or from the SERL participant survey. Table 7 lists the independent variables we have included in this analysis and the hypothesised reason that we expect them to influence the outcome.

Table 7 Initial list of variables and reasons for inclusion in regression analysis.

Variable	Reason for including
EPC lodgement date	We expect that a home with an older EPC is more likely to have had energy efficiency upgrades, e.g. a new boiler, or new windows. Therefore we expect that older EPCs will tend to be less accurate

[51] Huebner, G. M. et al. (2015) 'Explaining domestic energy consumption - The comparative contribution of building factors, socio-demographics, behaviours and attitudes', Applied Energy, 159, pp. 589–600. doi: 10.1016/j.apenergy.2015.09.028.
[52] McKenna, E. et al. (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, p. 111845. doi: 10.1016/j.enbuild.2022.111845.

	than newer ones. Note, scenarios 3 and 4 account for recent upgrades.
Lodgement purpose	EPC assessments carried out for new homes are generated using full SAP and so may be more accurate, assessments for ECO or grant schemes may indicate that a change to the building happened soon after the assessment. After initial analysis we did not include this variable as the majority of EPCs in our analysis were for ‘marketed sale’
Thermostat temperature	Homes that are heated to a different temperature than SAP assumes would use significantly different amounts of energy even if the rest of the model was correct. We code this variable as the difference between the SAP modelled temperature for zone 1 (21C) and the self-reported thermostat temperature. Note this is accounted for in Scenario 4.
Whole home heated indicator	SAP assumes that the whole home is heated so any deviation from this could have a significant impact.
Occupant number	SAP assumes a number of occupants for the home based on the floor area. This impacts the modelled amount of cooking, appliance and hot water use, so any deviation from the modelled number could be significant. We code this as the difference between the SAP modelled number of occupants and the number of occupants according to the self-reported survey. Note that the SAP model of occupancy gives floating point numbers whereas the survey gives whole numbers so when we categorise the SAP model as being equal to the actual number of occupants we mean it is within +/-0.5.
Financial wellbeing	SAP assumes that enough heating is used to reach the specified demand temperature in the heating hours, however ability to pay for household bills and other expenses may limit the extent to which people are willing and able to use this much energy. SERL participants are asked the following question: “How well would you say you yourself are managing financially these days? Would you say you are… Living comfortably / doing alright / just about getting by / finding it quite difficult / finding it very difficult / don’t know / prefer not to say”. Participant responses categorised as either ‘comfortable’ for the first three responses or ‘struggling or no answer’ for the last four responses.

Floor area	Floor area has a substantial impact on energy use, however for this analysis the dependent variable is normalised by floor area so we do not include it as an independent variable.
Building age	Building age is one of the key parameters used to determine the U-value associated with building elements in RdSAP so can have a significant impact on the modelled energy use.
Wall type	The heat loss through walls is one of the most significant components influencing space heating and the U-value of walls is determined by a combination of wall type and building age in RdSAP.
Floor type	The floor type influences the fabric and ventilation heat loss.
Roof type	The roof type includes the amount of loft insulation (if applicable) and can have a significant impact on the heat loss. Moreover, if the loft is not accessible then loft insulation thickness will be assumed based on the age of the property.
Modelled mean internal temperature	The modelled mean internal temperature is based on the modelled heat loss and heating controls, it determines the amount of energy required to heat the building in the model. This means it is strongly related to the modelled energy use.
Modelled air change rate	The modelled air change rate is a significant component in the overall heat loss associated with a building, particularly for older homes. It is likely to be strongly related to the modelled energy use.
Modelled heat loss parameter	The modelled heat loss parameter directly influences the modelled energy use.
Modelled hot water system efficiency	Hot water use represents the only form of energy used inside the building that does not ultimately contribute to internal heat gains as heated water leaves the building (apart from hot water cylinder standing losses in the case of system boilers). The hot water system efficiency is particularly important to the summer gas use since there is little else that uses gas in the summer.
Modelled main heating system efficiency	The efficiency of the main heating system is directly related to the amount of delivered energy required to heat the building.
Modelled proportion of total energy use for space heating	If the proportion of total energy use for space heating is not accurately captured by the model this could have an impact on the scale of the gap, particularly if the assumed heat loss is not accurately captured.

Modelled proportion of total energy use for water heating	If the proportion of total energy use for water heating is not accurately captured by the model this could have an impact on the scale of the gap, particularly because hot water does not all contribute to internal gains.
Modelled proportion of total energy use for secondary heating	If the proportion of total energy use for water heating is not accurately captured by the model this could have an impact on the scale of the gap, particularly because secondary heating efficiency will likely be different to the main heating system efficiency.
Hot water system type – combi or system boiler	System boilers have a hot water tank and the heat loss from this contributes to space heating in the winter but is wasted energy in the summer. If the heat losses associated with the system boiler are not well modelled this could significantly impact the modelled energy use and subsequently the gap. This effect may be most apparent in a model of the base energy use intensity.

It is likely that several of the variables listed in Table 7 are correlated. To avoid issues associated with multicollinearity in linear regression models (i.e. wide confidence intervals and misleading coefficients), we initially investigate which variables are correlated using variance inflation factors (VIFs). VIF values over 5 indicate strong multicollinearity for a variable, and we successively excluded the variables least likely to be directly related to the performance gap[53]. The final list of variables included in the analysis is given below:

- Building age
- Wall type
- Floor type
- Roof type
- Hot water system type
- Proportion of secondary heating
- Whole home heated indicator
- Financial wellbeing
- Difference in thermostat set point between SAP and survey
- Difference in occupant number between SAP and survey

Using the subset of non-correlated variables, we fit a model of the performance gap, of the form:

$$\Delta E = \alpha_0 + \alpha_1 x_1 + \cdots + \alpha_N x_N$$

[53] Note that in subsequent parts of the analysis the heating system efficiency is shown to be important in the gap. As a result, we investigated adding this variable into back into the analysis but in order to maintain uncorrelated inputs it would have been necessary to remove both building age and wall type from the analysis.

Where *ΔE* is the difference in metered and modelled energy use intensity, *xi* are the set of *N* independent variables, and *αi* are their modelled coefficients.

Since we anticipate that the factors influencing the performance gap may be different for different types of energy use, we repeat the analysis using both the difference in the HPLP and the baseline energy use intensity and present the results of these in Appendix A. The difference in the HPLP is related to the heating energy use, and the baseline energy use intensity to the summer hot water, lighting and appliance use. The performance gap is also likely to be affected by the updates to the model, so we also generated the results using the model scenario 4 results; these are also presented in Appendix A.

For all regression models we consider coefficients statistically significant if they have a p-value ≤ 0.05. We further examine the goodness of fit using three indicators: the R^2 and adjusted R^2, the mean absolute error and the root mean square error.

The regression analysis was carried out using the *statsmodels* package in python.

Forensic investigations

The forensic investigations included collecting detailed building and occupant data in 40 homes via an occupant energy use interview and a full SAP assessment of the building fabric and energy services, undertaken by an Expert Assessor.

The forensic sample was selected from the existing SERL Observatory, from homes meeting the filters required for inclusion in the smart meter data analysis. An additional filter was applied to target homes primarily in the West Midlands and North West of England as this minimised the travel times for the Expert Assessors. Recruitment for the 40 gas heated homes took place between July 2024 and January 2025, while recruitment for the 5 electrically heated homes took place in January 2025. Potential participants received an invitation letter explaining the project, details of participation requirements and offering a £50 ‘thank you’ to those agreeing to take part and commit to a 3-hour visit from the Expert Assessor. A single reminder letter was sent approximately 2 weeks after the initial letter. The overall response rate was 18.8%. The sample was selected to span a range of building types and ages, Table 8 shows some of the key characteristics of the recruited homes.

Table 8 Key characteristics of the homes recruited for forensic analysis.

EPC band	N	Dwelling age	N	Number of habitable rooms	N	Property type	N	Built form	N
A & B	5	Pre-1900	5	2 to 3	6	House	30	Semi-detached	11
C	11	1900-1929	6	4	3	Bungalow	3	Mid-terrace	5
D	12	1930-1949	3	5	7	Flat	2	Detached	16
E	5	1950-1966	4	6	6			End-terrace	3
F & G	2	1967-1975	0	7	4				
		1976-1990	4	8 or more	4				
		1991-2002	0						
		2003 onwards	0						
		No data (new home)	5						

The Expert Assessors visited the recruited households and carried out a full SAP assessment, as well as collecting additional data likely to be needed for HEM. Prior to their visit the Expert Assessors were given the historic EPC inputs (as well as being able to access the standard EPC registry) to check if the previous assessment was correct according to best practice. They also identified whether changes to the building had been made since the historic assessment. The inputs from the expert SAP assessment were then used to investigate the impact of the process and SAP assumptions on the gap by incrementally modelling the changes from the original EPC to the status as in 2021.

During the visit the Expert Assessors carried out a 30-minute interview with the householder, the contents of which was agreed in collaboration with DESNZ. The purpose of the interview was to establish whether there were any significant deviations in terms of energy use compared to the assumptions in the SAP model, so the interview focussed on the main energy uses including heating and domestic hot water habits, noting any usual appliances likely to use significant amounts of energy, and the typical occupancy in the home. The interview also established the history of any home improvement measures such as extensions or room conversions and any energy efficiency improvements such as replacement windows or heating systems. Using this history the Assessor provided several versions of the full SAP model, including for the home as found, as in 2021 for comparison with the metered data, and as it was when the previous EPC was carried out. The Expert Assessor made notes on the interview using the proforma provided in Appendix K.

We also compare the metered energy data with the modelled energy use according to the expert EPC assessment and the original EPC assessment to explore the impact of the expert EPC assessment on the performance gap.

Internal temperature analysis including predicted internal temperatures

SAP calculations predict the Mean Internal Temperature (MIT) in a building from a number of parameters including the demand temperature, heating hours, and the efficiency of the building fabric. The difference between MIT and default regional external temperature is then used to calculate the space heating demand. For further discussion of the MIT calculation and a description of key parameters, see Appendix J.

It is widely recognised that the SAP algorithm for MIT is a relatively simple steady state model, with multiple assumptions relating to occupancy and the distribution of heat throughout the dwelling, as well as the ventilative and fabric heat loss. Many of these approximations and assumptions have been the subject of much debate over the period that SAP has been used and developed. Together, these approximations and assumptions could result in significant errors. A widely held hypothesis is that the performance gap is attributable to occupants underheating compared to SAP assumptions, particularly in poorly insulated homes, either because they cannot afford to, or the heating system is undersized. This could be because occupants reduce thermostat temperatures, however SAP assumes lower set point temperatures in Zone 2 of the building depending on the Heat Loss Parameter (HLP) and heating control, so this effect could already be accounted for.

Previous analysis undertaken by Few et al. (2023) has tried to address this question by using self-reported thermostat setting data. However, there were several limitations in this approach, including that self-reported thermostat data is not necessarily a good representation of the achieved or the mean internal temperature. In addition, internal temperature data was not recorded in the homes available to the Few et al. (2023) study, and the SAP modelled MIT is not available in the EPC registry.

This work stream overcomes these limitations by analysing monitored internal temperature collected by EFUS, and compares this with modelled monthly mean internal temperatures predicted by SAP/NBM-SERL. EFUS/EHS contextual data is analysed to observe how self-reported set point temperatures relate to MITs. Figure 15 shows a schematic diagram of this part of the analysis. Note, temperature data analysis was also undertaken on an additional GHG-SMETER field trial data set to test the validity of the EFUS results, see Appendix F for details of the data cleaning, analysis and results from this additional data set.

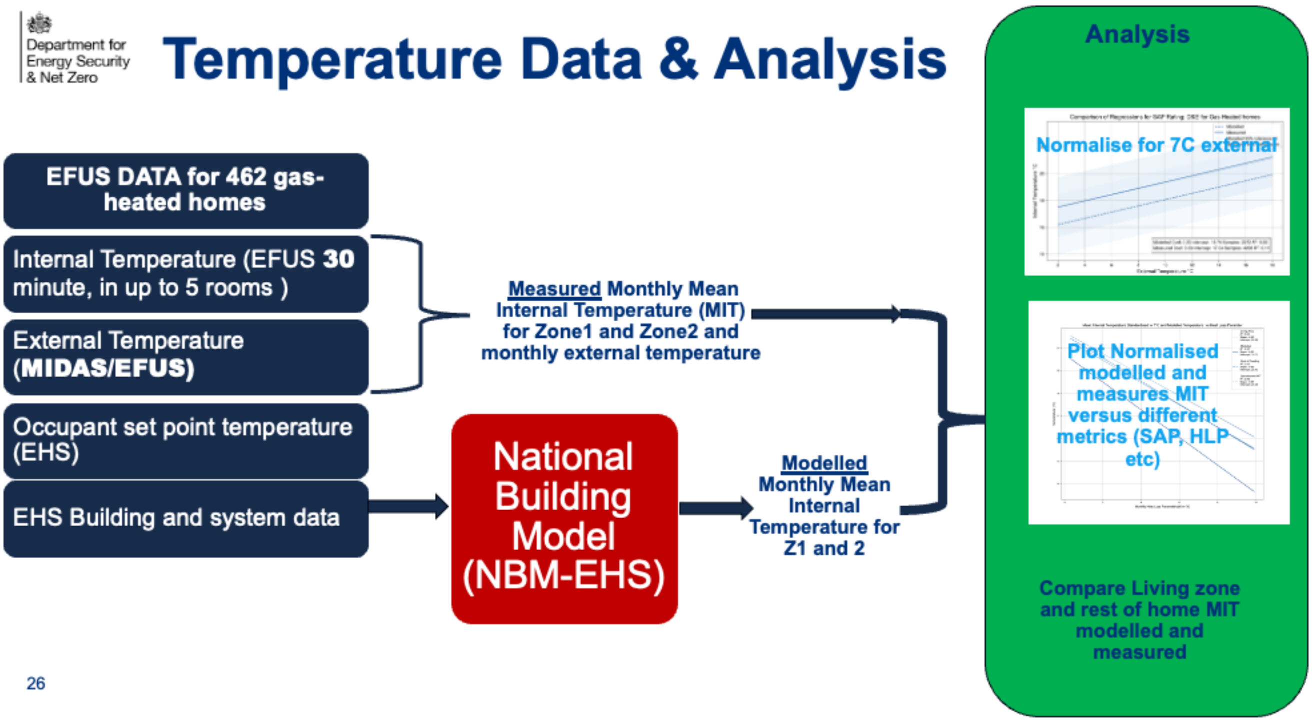


Figure 15 Schematic of EFUS temperature data analysis

Temperature Data cleaning: EFUS

The EFUS data was provided to this project in long form and some data cleaning had already been carried out, which has been described within the EFUS 2017 Methodology Report[54]. Briefly however, data was excluded where the loggers were recorded as being in rooms that did not exist for the dwelling, or that were not the intended room, in cases where the logger was thought to be malfunctioning (temperatures of higher than 50°C for extended periods, or loggers that had failed and were recording temperatures of -45°C). Data was also excluded where loggers were returned too late, or the logger IDs did not match the interview IDs for a particular dwelling. Effects such as loggers being potentially moved (indicated by a step change), solar radiation being incident on the sensor, and occupants likely being absent were not accounted for during this initial cleaning.

For the purposes of this analysis, it was thought to be important to fully exclude the effects of solar radiation being directly incident on sensors. This is because not only are the initial effects substantial (with 20°C change from background temperature), but it can take time periods of the order of days for the sensor to recover. Furthermore, the sensors are placed in specific locations that are close to internal walls. If a sensor is affected by solar radiation, it is likely that the wall behind it is also affected. This means that temperatures recorded by the sensor affected by gains may not be representative of the room temperature due to radiant heat from

[54] Department for Business, Energy & Industrial Strategy (BEIS). (2017). Energy Follow-Up Survey 2017: Methodology Report. Conducted by BRE. Authors: Justin Allen, Adele Beaumont, Matt Custard, Helen Foster, Helen Garrett, Andrew Gemmell, Sami Kamal, Susie Margoles, Emma Munkley, and Felicity Taylor. Available at: https://assets.publishing.service.gov.uk/media/65312efc26b9b1000daf1bea/efus-methodology-report.pdf

the wall, and even on days when solar radiation is not directly incident on the sensor it is still possible that the wall may be absorbing and radiating heat.

For this reason, any rooms where significant solar effects were observed were excluded entirely from the analysis. Due to the diversity of heating patterns and behaviours, it is very challenging to algorithmically distinguish between the effects associated with heating systems, and solar effects. For the purposes of this project therefore solar was excluded by manual inspection of the internal temperature data. Any data where the temperature was higher than 35°C was also excluded.

Following this cleaning procedure and filtering for homes which had mains gas heating, there were 462 dwellings.

Times during which occupants were assumed to be absent, or the heating was not on, or during which the set point appears to change were not excluded. The justification for this is that heating patterns are extremely variable, and occupants may be present in the dwelling but not heating it, or they may be varying their thermostat set points in other ways that although not well represented by SAP assumptions, are still valid internal temperatures that are important to analyse. The statistics have therefore been constructed from all available data, with unheated periods of data, as well as portions which have different heating patterns making up a portion of the overall statistics.

Mean Internal Temperature (MIT)

The MITs have been calculated for each dwelling for all available rooms on the basis of aggregations over different time periods. For the purposes of comparison with SAP-NBM modelled outputs, monthly mean temperatures were constructed for the whole dwelling, Zone 1, and Zone 2. Zone 1 was interpreted as the living room, and Zone 2 was interpreted as being the remaining available rooms.

To assess the SAP heating schedule, Monthly MITs were calculated for each of the time periods that the heating is assumed to be “on” for Zone 1 and Zone 2 for weekdays and weekends. During the week, heating is assumed to be on from 07:00–09:00 and 16:00–23:00, and between 07:00–23:00 at the weekend. The demand temperature is 21°C for the living area during these times.

Linear regressions on both Measured and Modelled monthly MITs against monthly external temperatures were also performed, disaggregated by different building characteristics as recorded in the NBM/SERL metadata.

Predicted Internal Temperature

In order to make a fair comparison between dwellings that are located throughout the UK, and are thus exposed to different outdoor temperatures and weather conditions, it is necessary to make an attempt to generate a temperature metric for each dwelling that as far as possible is independent of the regional weather and temperature variation.

To do this, a Predicted Indoor Temperature was calculated for each dwelling using linear regression, and using elements of the method developed in Oreszczyn et al., (2006)[55]. In summary, the approach for each dwelling is as follows:

- Calculate Mean Monthly temperatures for each dwelling for each room, and for each of the SAP defined zones; the Living area (Zone 1), the Rest of the Dwelling (Zone 2) and the whole dwelling (Mean Internal Temperature), as well as a mean monthly external temperature.
- Perform a linear regression on for each dwelling for each zone against the mean monthly external temperature, for the heating season months.
- Predict the indoor temperature for each dwelling using the calculated regression coefficients for an external temperature of 7°C, because it is indicative of a 'typical' heating day.

This approach facilitates evaluation of the impacts of different dwelling characteristics on indoor temperatures, in the absence of the strong driver of outdoor temperature. In the case of EFUS, data describing the global horizonal irradiance was not available, however a future analysis may account for this and improve predictions.

Finally, throughout this and the smart meter energy analysis rigorous Statistical Disclosure Control procedures were adhered to. This is critical in the protection of participant identity and is fundamental to handling sensitive data. For this reason, no data point that could identify specific dwellings or households is released, and statistics for non-derived variables are calculated for a minimum of 10 dwellings. In the case of medians and percentiles, SERL and ONS guidance is followed, which allows medians to be released if there are more than 20 individuals represented. 25th and 50th percentiles are required to have a minimum of 10 data points either side. Histogram bins containing fewer than 10 data points are excluded.

Analysis of EPC registry data

Homes can have several EPCs which may be collected at different times and for different purposes. Both the time of lodgement and purpose (denoted as the 'transaction type' in the dataset) are lodged in the registry. We identified two main groups of homes from the registry:

- Homes with a transaction type of 'new dwelling' and a subsequent 'marketed sale' transaction
- Homes with multiple 'marketed sale' transaction types

The first group are important because EPCs for new homes are (usually) generated using the full SAP process, whereas those for marketed sale generated using RdSAP. The 'new dwelling' category is also used in cases where a change-of-use from non-domestic to domestic

[55] Oreszczyn, T., Hong, S. H., Ridley, I., & Wilkinson, P. (2006). Determinants of winter indoor temperatures in low-income households in England. Energy and Buildings, 38(3), 245–252. https://doi.org/10.1016/j.enbuild.2005.06.006

has taken place, in such instances an RdSAP can be used instead of a full SAP. As a result, we excluded all cases where the construction age was prior to 2002 to remove as many of these change of use cases as possible and focus our analysis on newly built homes rated via SAP (note that age bands closest to the start of the data in 2008 is 2003 - 2006 and 2007 - 2011, we included the previous age band to allow for the period of construction). We also selected homes with 'NO DATA!' in the construction age field, as this is very common for newly built homes. Some homes had multiple 'new dwelling' EPCs and we selected the most recent EPC for further analysis in these cases. This group is also useful because, it is unlikely that changes would be made to new homes that would significantly decrease their energy efficiency.

The second group have been rated by RdSAP on multiple occasions so can help to identify the changes associated with different versions of RdSAP. Figure 16 shows a histogram of the time between one EPC rating and the next per household, showing a very significant peak close to zero. We suspect this is because of small errors being noted in the lodged EPCs and assessors providing a corrected one very quickly. The peak drops very close to the background level of repeated interventions after approximately 60 days. In cases where there is a subsequent EPC less than 60 days since the previous one, we keep the later EPC only. Also note the large peak around 10 years reflecting the validity period for EPCs.

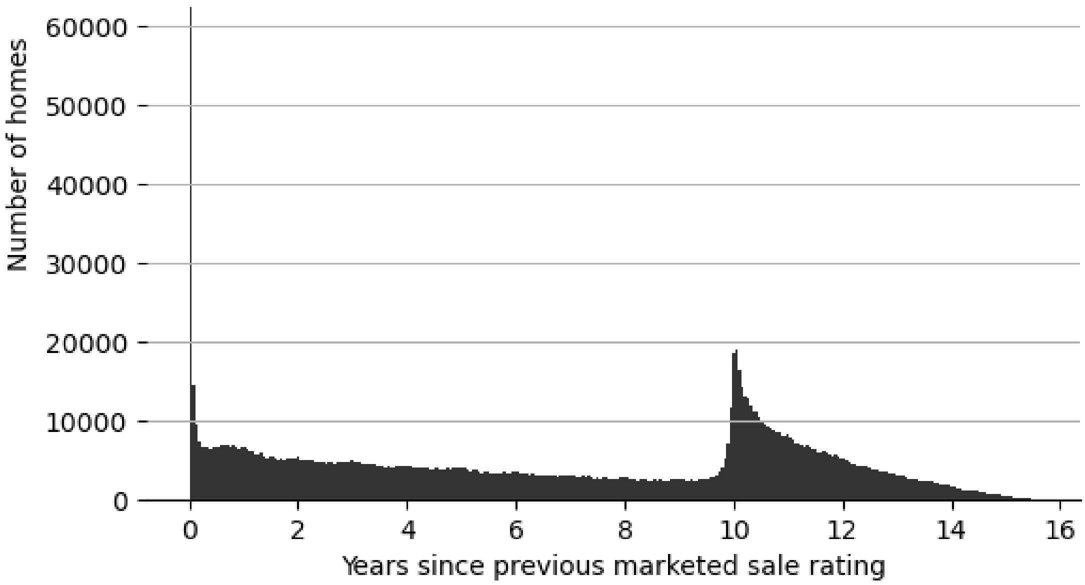


Figure 16 Histogram of the time between marketed sale ratings for the same home.

We compare a number of parameters between the first and second ratings to understand the difference in outcome between the two types of ratings. Firstly, we compare the current energy efficiency (sometimes called the SAP score) and the current energy rating (sometimes called the EPC band). We determine whether there is a statistically significant difference in the means between the current energy efficiency using a t-test.

To further investigate changes from one rating to the next we used the energy efficiency ratings of different building elements on each EPC. These ratings are presented as a star rating between 1-5 on the EPC and as categories from very poor to very good in the EPC registry. The relationship between these ratings and the physical parameters associated with the element they refer to is not published publicly. However, the conversions for several versions of SAP and RdSAP were provided by DESNZ for the purpose of this project. Conversions were available for RdSAP 9.91, RdSAP 9.92 and SAP 10.2. The documents note any changes since the previous version, and so in some cases it was possible to infer the values for RdSAP9.90, and if there was no change between the values in RdSAP 9.92 and SAP 10.2 it could be inferred that the intervening versions had no change either. We were then able to identify periods over which the meaning of the ratings was consistent and select homes with a 'new dwelling' and subsequent 'marketed sale' rating during this stable period. The ratings were then compared for the given element when rated as new and subsequently for marketed sale to investigate the parameters that had changed from one rating to the next.

Validating results

The analysis is complex involving many different data sets involving several hundred different variables, which have been linked and filtered in different ways and then linked to complex models or undergone complex analysis. As a result there is potential for errors, and we have identified some errors since the first results were preliminarily released. We have sense checked the key results as much as feasible, and have looked for evidence from other published sources and also undertaken comparative analysis from similar data sets where practical. In particular, we have undertaken the following:

- Compared the NEED metered energy data with SERL smart meter data for identical properties, see Appendix H
- Compared EPC input parameters that are lodged in the EPC database with those that are lodged in NEED for the same house, e.g. property age, storey height, floor area, see Figure 6 in the background section
- Compared the NMB-SERL SAP ratings with those lodged by the commercial EPC assessor. We have only used results for homes where NBM-SERL and commercial SAP value agree within 2 points (this is the case for over 95% of cases), see Appendix E
- Compared MIT measurements in the EFUS database with similar measurements for GHG-SMETER database, see Appendix F
- Compared the performance gap, and key variables observed analysing the NEED database of 300,000 homes in London with SERL analysis. NEED has a much larger sample but only has annualised energy data not monthly, see Appendix G.

Results – Part 1 Gas Heated Homes

This section presents the results of the different methods of analysis:

- SAP energy use compared to smart metered data and comparison of energy signature parameters
- SAP modelled Mean Internal Temperature (MIT) compared to metered MIT
- Variation between original historic EPC RdSAP assessment and a full SAP assessment. (Forensic analysis)
- Variation of lodged EPC assessments over time and between RdSAP and a full SAP.

Note that where possible analysis has been undertaken at either the annual or monthly timescale as this is the timescale on which SAP makes predictions. Since the SAP calculation normalises for floor area, we also use energy use per unit of floor area, or Energy Use Intensity (EUI) as the key comparison for the performance gap.

We have banded much of our analysis according to EPC rating (A to G) as policy makers are most interested in how homes may have been mis-rated. However, the EPC Energy Efficiency Rating (EER) is based on a complex algorithm that is based on fuel cost, not energy consumption, and has the additional complexity of standing charges and a logarithmic function so it is complex to interpret from a building physics perspective. Also, the energy metric for future EPCs could be changed, so in addition to banding by EPC band or SAP rating we have used other criteria for banding that enable the core algorithms underpinning SAP to be better investigated.

We have calculated the performance gap separately for gas and electricity as summer gas uses is indicative of hot water energy use (plus a small bit of gas cooking). Electricity use shows how lights, appliance and cooking energy use vary both seasonally and with occupancy. Note, only gas heated homes have been included in most of the analysis presented in this report.

We have colour coded all gas data using a blue colour scheme, electricity data as purple, and total energy use as orange. We have also used the colour coding for EPC bands as shown on the EPC Certificate.

SAP energy use compared to metered data

Annual analysis

Figure 17 below shows the electricity and gas use for each model as a proportion of the final model (scenario 4) total energy use. The figure shows that the metered energy use is by far the lowest, representing 87.3% of the energy use modelled in scenario 4. Scenarios 0, 1 and 2 show very similar overall energy use, while the greatest change in the modelled energy use is from model 2 to 3. Model 3 includes energy efficiency retrofits through government schemes as recorded in NEED, the significant change in modelled energy use when these retrofits are included in the modelling suggests that many homes have been improved since the EPC was generated. The change from this to model 4 which also incorporates the actual number of occupants and the thermostat temperature from the SERL survey is relatively small. However, for model 4 it should be noted that, as described in the NBM-SERL methods section, the target temperature was changed for Zone 1 only, the target temperature in Zone 2 was not adapted.

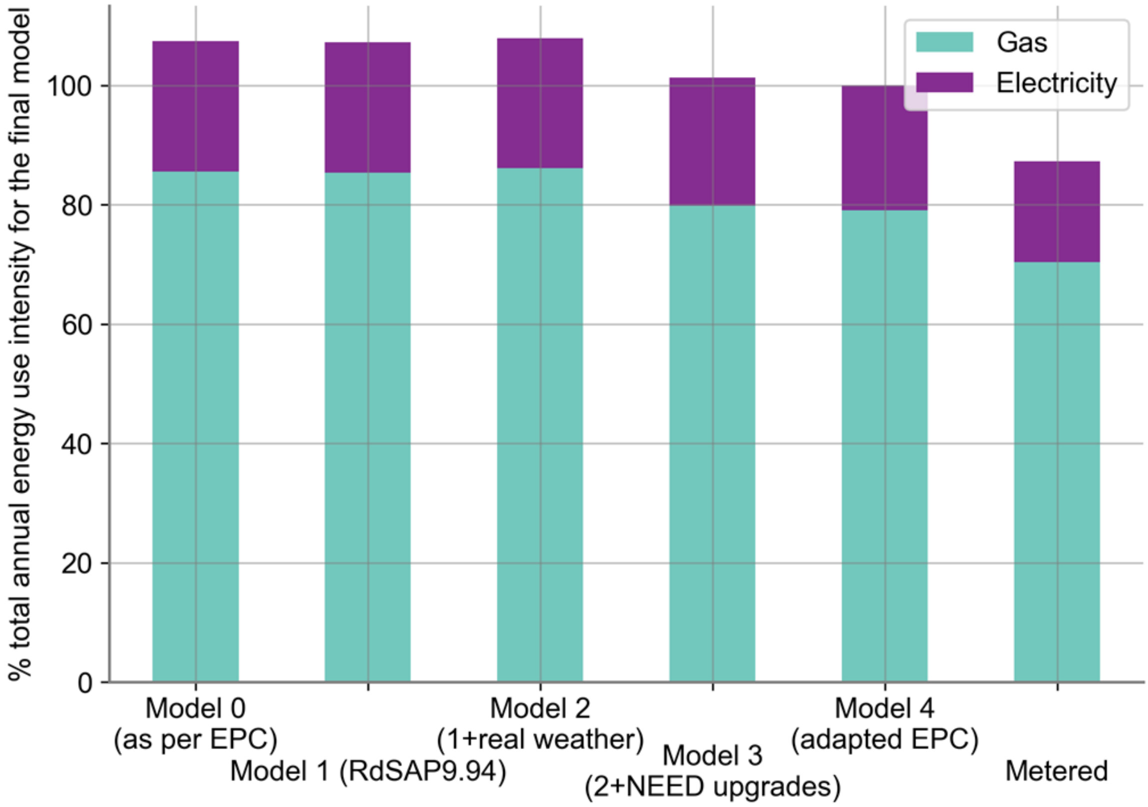


Figure 17 Electricity and gas use as metered and modelled under each scenario as a proportion of the total energy use modelled in scenario 4.

Figure 18 below shows a histogram of the percentage difference in metered-modelled energy use for model 0 and model 4. While both models show a clear skew towards negative values (meaning the modelled energy use greater than metered), the skew is reduced for model 4. In both cases the distribution is wide, showing that there is considerable variability in the agreement between metered and modelled data on an individual household level.

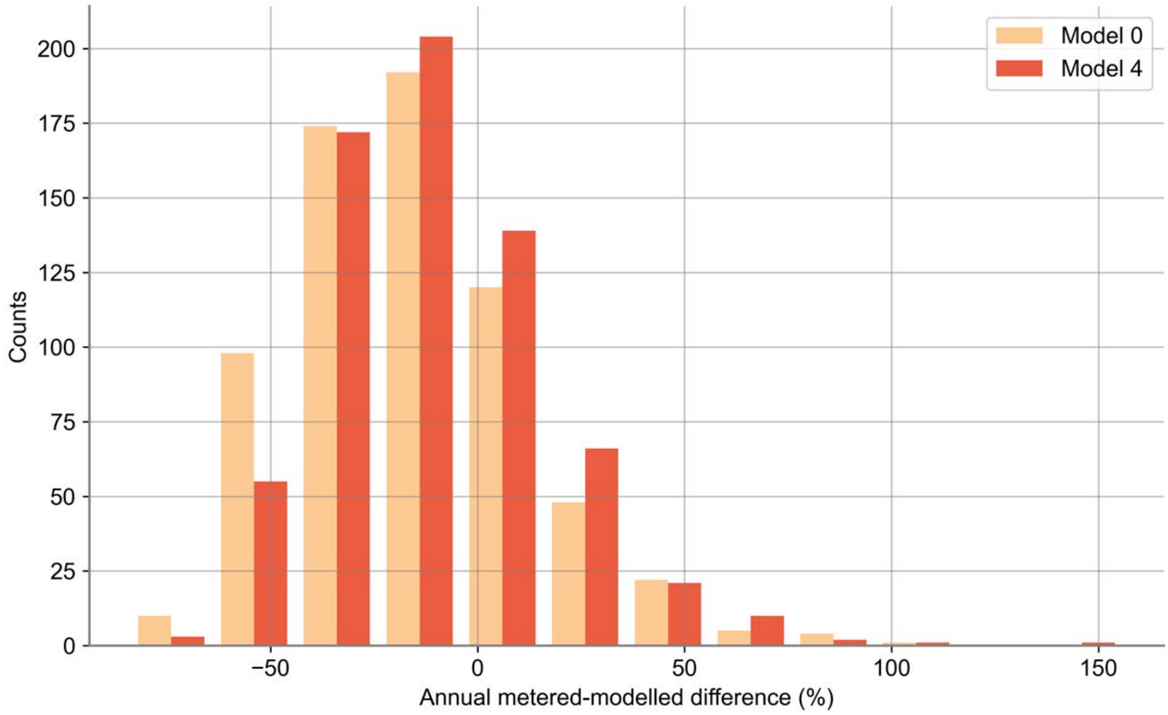


Figure 18 Histogram of the annual percentage difference in metered-modelled energy use for model 0 and model 4.

Figure 19 shows the total delivered energy use intensity (EUI) of the metered data and each of the modelled scenarios. For all EPC bands and under all scenarios the average modelled EUI is greater than the metered EUI within the error bars. The metered EUI shows a modest increase when moving from the most efficient to least efficient EPC bands, while the modelled EUI shows a much steeper increase across EPC bands.

The change in average modelled energy use between models 0, 1 and 2 is relatively small, becoming slightly larger for homes rated as E, F or G, although the difference is still within error bars. Model 3, which incorporates energy efficiency upgrades lodged in the NEED database, shows noticeably smaller differences between metered and modelled energy use for bands D to F and G. This suggests that many of the homes which are rated as inefficient have been improved since the EPC was generated. The change associated with model 4, incorporating the actual occupancy number and the thermostat set point is modest for all bands.

We find that on average model 0 gives an average performance gap of -16.0%, however for band C homes the gap is -6.6% while for band E homes the gap is -34.3%. For model 4 the overall performance gap drops to -10.9%, for band C to -4.4% and for band E to -23.5%. The improvement in the outcomes, as a result of the updates to the model, are largely associated with model 3.

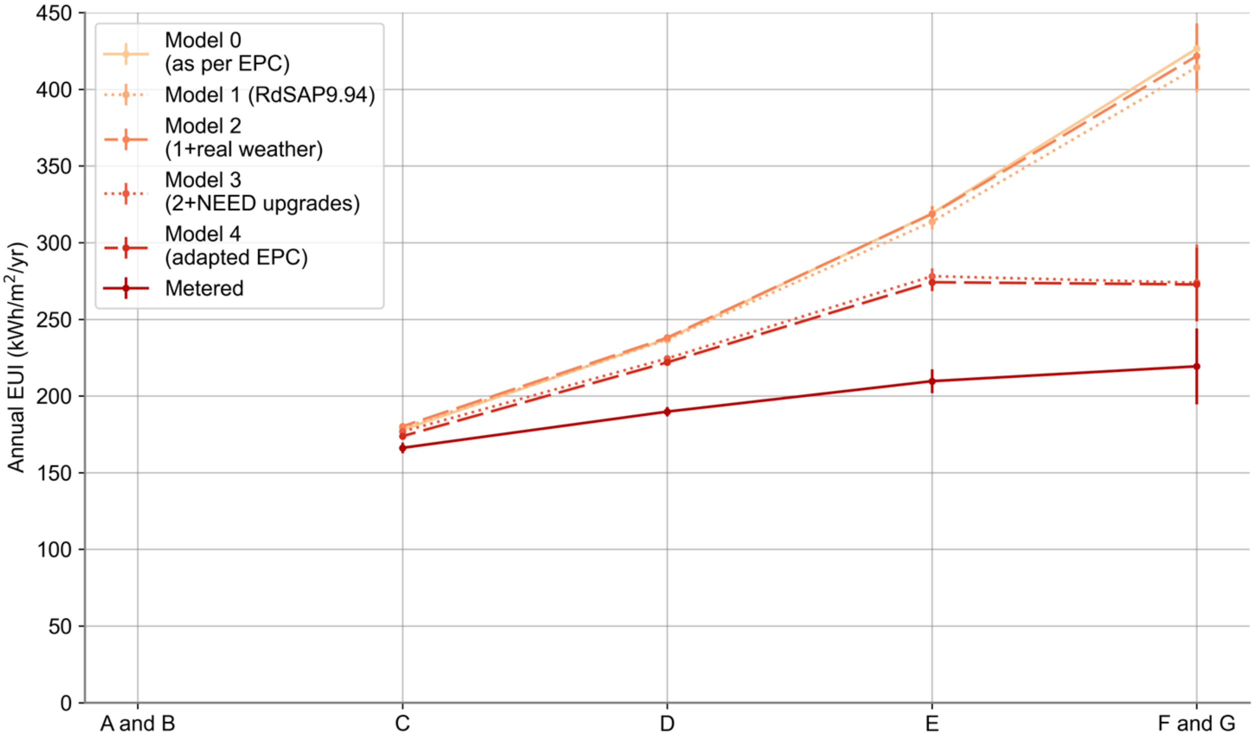


Figure 19 Annual total energy use intensity for EPC bands under each of the modelled scenarios and as metered in 2021. The points and bars represent the mean and standard error on the mean respectively.

Figure 20 shows the total delivered gas energy use intensity of the metered data and each of the NBM-SERL modelled scenarios. The trends are very similar to the total EUI reported in the figure above. However, the average gas EUI as metered and modelled is very similar under all scenarios for band C, and for bands F and G the metered gas use agrees with model scenario 3 and 4 within the error bars.

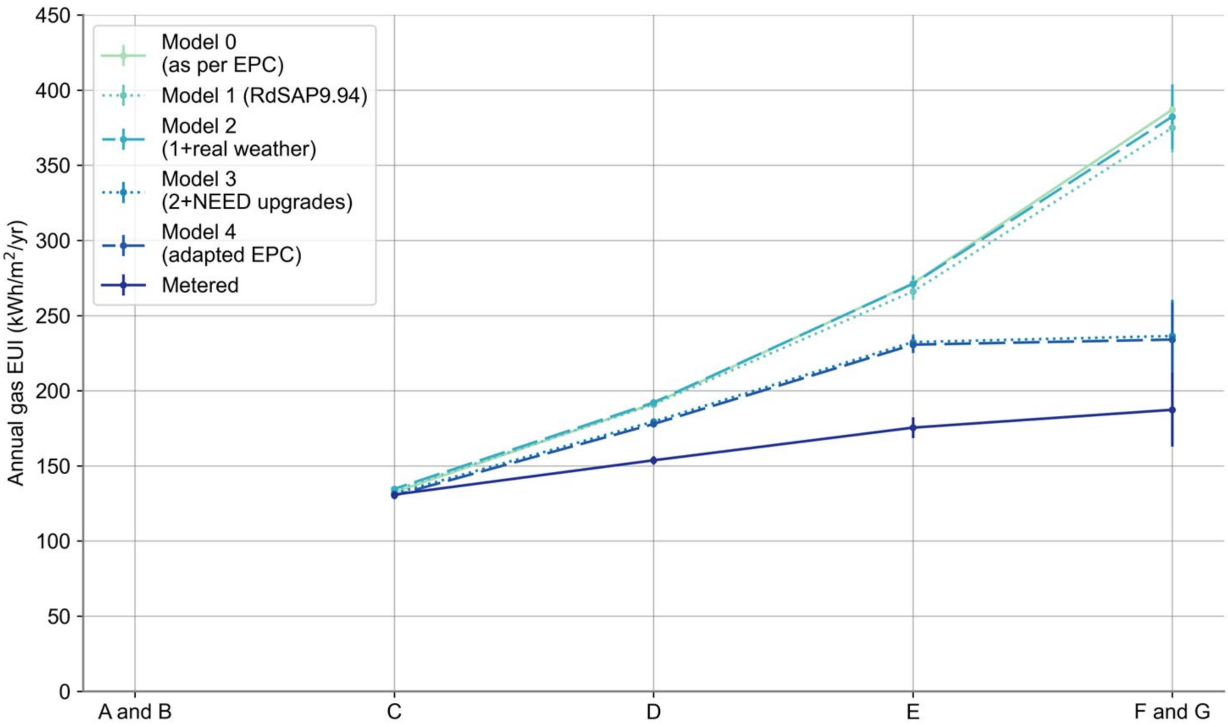


Figure 20 Annual gas energy use intensity for EPC bands under each of the modelled scenarios and as metered in 2021. The points and bars represent the mean and standard error on the mean respectively.

Finally, Figure 21 shows the total delivered electricity energy use intensity of the metered data and each of the NBM-SERL modelled scenarios. The metered annual electricity EUI is very similar for all EPC bands, and consistently lower than the modelled electricity EUI. The EUI for all modelled scenarios is very similar, with the largest change observed for homes in band E for model 4. Model 4 adapts the EPC according to the actual number of occupants. The number of occupants impacts the appliance and cooking use in the SAP model so would be expected to have some impact on the electricity use.

It is worth noting that the only energy metric which is reported on the public EPC record is the primary energy use intensity (PEUI), and this weights electricity use 3 times more than gas. This means the discrepancy in PEUI is disproportionately affected by any differences in metered and modelled electricity use. Similarly, the main metric used by EPCs to classify homes into the A-G ratings is based on cost per m², and since electricity is ~4 times more expensive than gas a discrepancy in the electricity use has a disproportionate impact on the modelled cost for the building.

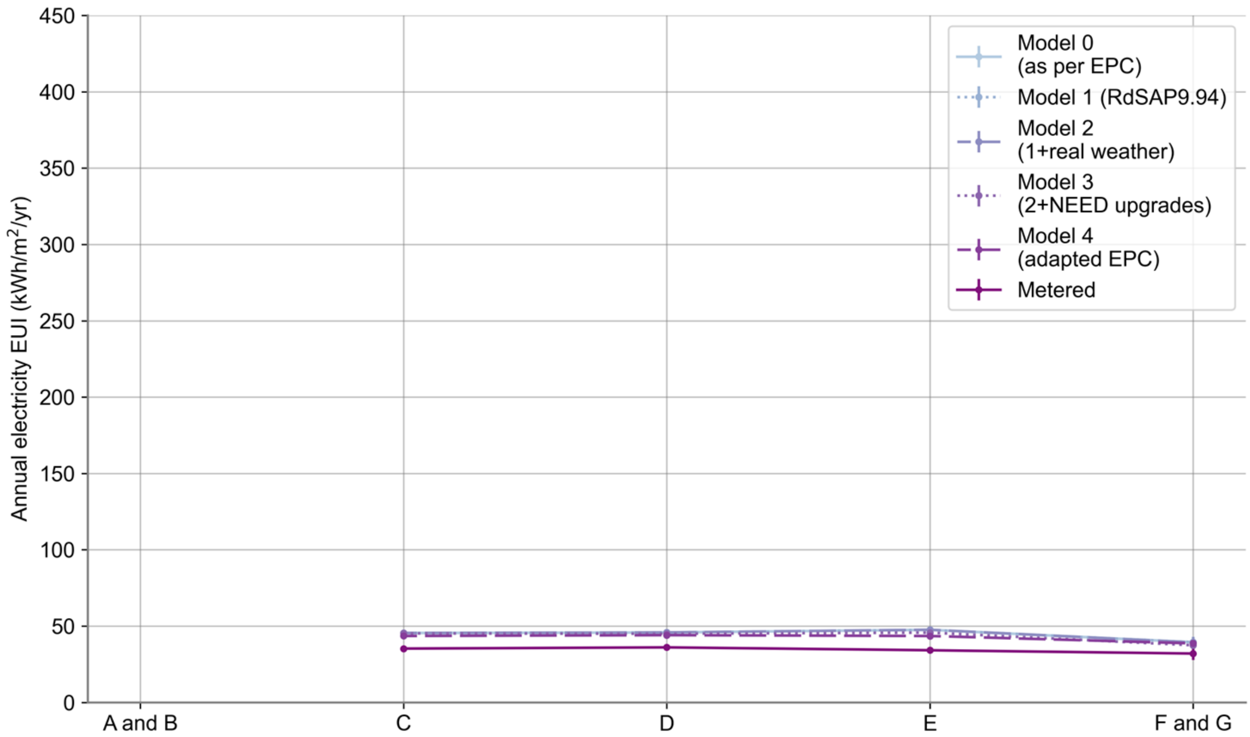


Figure 21 Annual electricity energy use intensity for EPC bands under each of the modelled scenarios and as metered in 2021. The points and bars represent the mean and standard error on the mean respectively.

Monthly analysis

Figure 22 below shows the average EUI in each month for total, gas and electricity energy uses, for the smart metered data and for the baseline model (as generated for the EPC) against the month. Figure 22 shows that during summer the metered gas use is higher than the model, while the metered electricity use is lower than the model. These effects are cancelled out for the total summer EUI and the metered and modelled total EUI agree closely. During the heating season, the metered gas EUI is consistently lower than the model, with the difference increasing in the middle of winter. The metered electricity EUI is somewhat seasonal, with greatest use in the middle of winter. The modelled electricity use is more seasonal than the metered electricity use, with the greatest discrepancy occurring in December and the smallest in July.

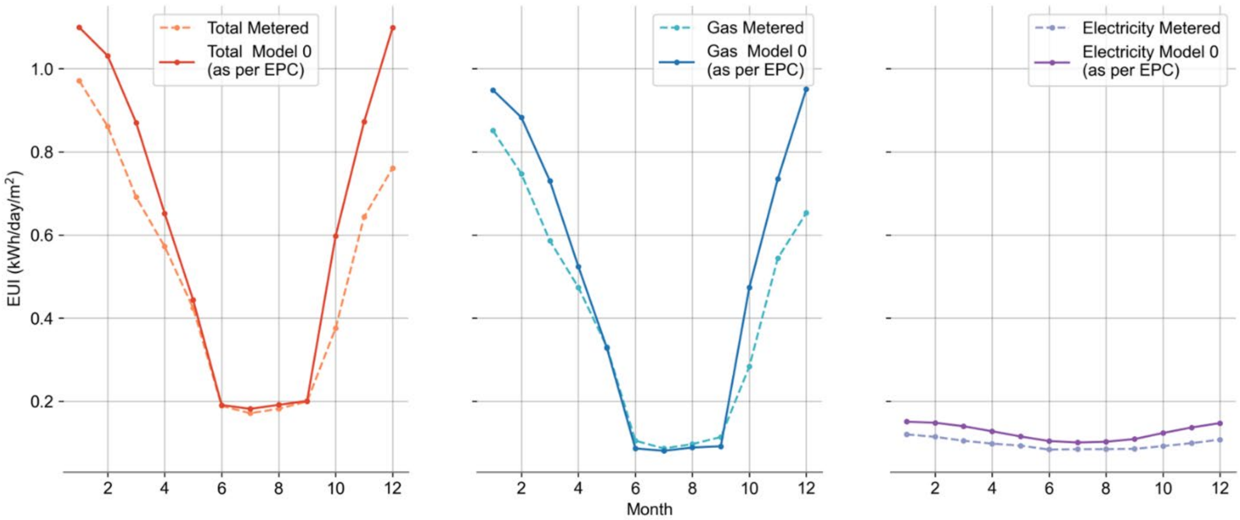


Figure 22 Monthly mean total, gas and electricity energy use intensity against month as metered and according to model 0 (as per the EPC).

Figure 23 shows the average EUI in each month for total, gas and electricity energy uses, for the smart metered data and for the baseline model (as generated for the EPC) against the external temperature. This shows that the summer temperatures were slightly warmer for the metered data than the model, and that the coldest month for the metered data was 1.1ºC colder than for the model. This figure also shows a distinctive step in the metered winter gas and total EUI. April 2021 was on average colder than March 2021, but the metered gas use was lower in April. April 2021 was the sunniest April on record, meaning that the solar gains would have been much higher than usual, and much higher than assumed by the SAP model.

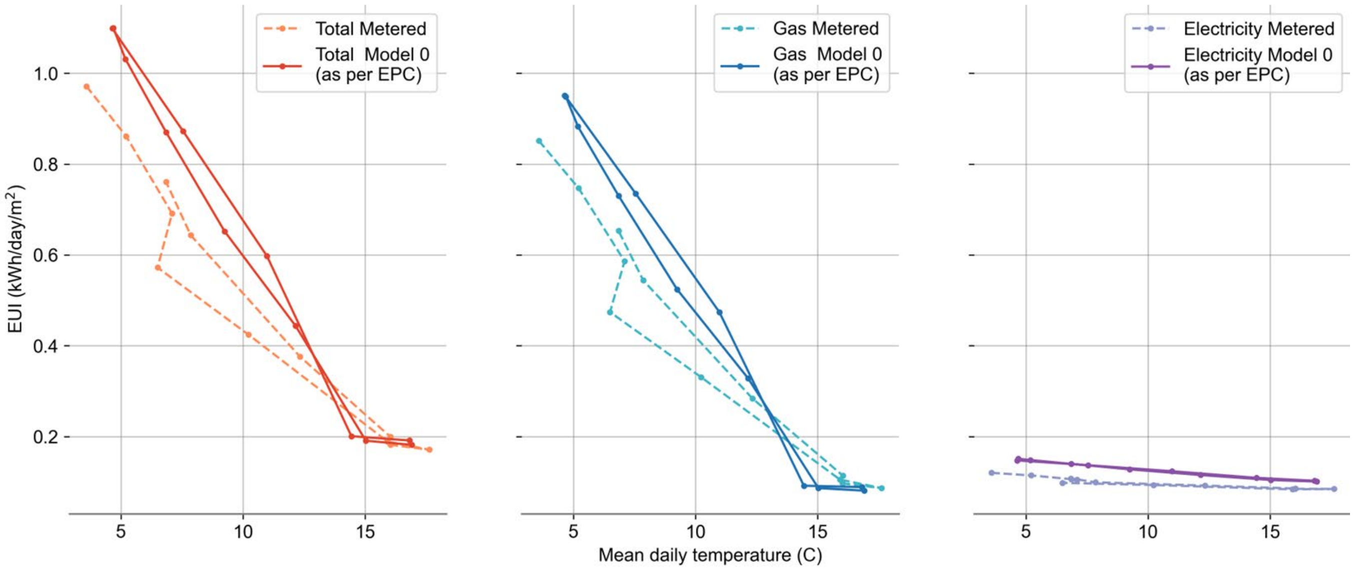


Figure 23 Monthly mean total, gas and electricity energy use intensity against monthly mean temperature as metered and according to model 0 (as per the EPC).

Figure 24 shows the monthly average energy use in each month for total, gas and electricity energy uses against the monthly mean external temperature for the metered energy and model scenario 4 (RdSAP9.94, actual weather, NEED updates, SERL occupancy updates). Compared to model 0 above, the discrepancy in winter EUI is noticeably reduced, although at all temperatures in the heating season the metered gas and electricity EUI remains lower than the model. The total summer EUI remains similar between metered and modelled while the metered gas is greater and electricity lower.

The modelled data for scenario 4 shows a clear drop in energy use in April, similar in shape to that observed for the metered data. However, the reduction in EUI is much greater in the metered data than the modelled, the metered EUI drops by 0.12 kWh/day/m² between March and April, whereas the modelled EUI drops by only 0.06 kWh/day/m², or by 47% of the metered drop. This suggests that the impact of solar gains may be underestimated in the SAP model.

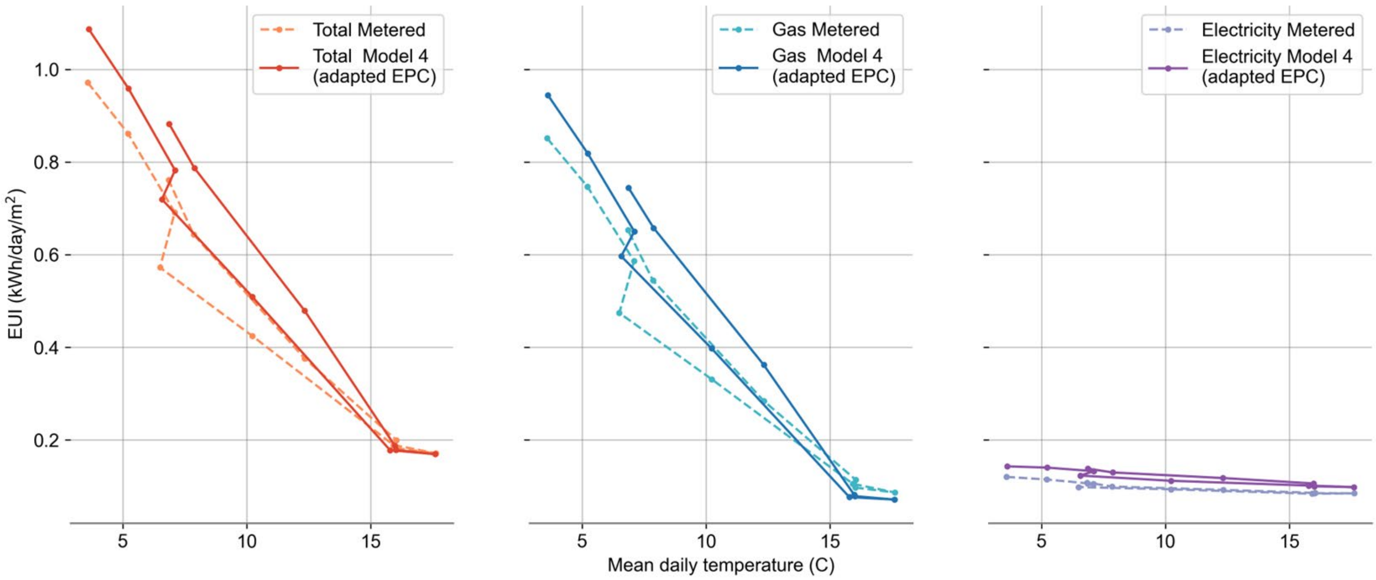


Figure 24 Monthly mean total, gas and electricity energy use intensity against monthly mean temperature as metered and according to model 4 (fully adapted).

Energy signature analysis: whole sample results

Figure 25 shows the distribution of the HPLP (Heat Power Loss Parameter), the balance temperature and the base energy use intensity for the metered and modelled scenarios. The HPLP decreases from model 0 to model 4. There is a large difference between the metered and modelled HPLP of almost 0.5 W/m²K. The decrease in HPLP for model 2 compared to models 0 and 1 is likely associated with the increased solar gains in the actual weather compared to the standard SAP assumptions as shown in Figure 23 above, this will tend to produce a lower gradient in the best fit line in the heating season. There is also a reduction in HPLP moving from model 2 to model 3, this is associated with the improved fabric and heating system efficiencies captured by the NEED data. The HPLP is very similar for models 3 and 4, this is expected because the changes to the occupant number and zone 1 demand temperature introduced in model 4 would have little impact on the HPLP.

The balance temperature is much lower for the metered data than any of the modelled scenarios, and the spread is also much greater. The balance temperature for the modelled scenarios is largely related to the external temperature in June and September because the SAP model assumes that heating is used consistently from October to May. As a result, the spread in balance temperatures is very small for all modelled scenarios. The balance temperatures for models using the same weather conditions are very similar (models 0 and 1, and models 2-4). In practice households will switch on the heating at variable times, resulting in the much larger spread in balance temperatures observed for the metered case. Moreover, the balance temperature is much lower than any of the modelled scenarios, suggesting that typically heating is used for fewer months than is anticipated by the SAP model. Note that this also has implications related to the internal temperature, however, we defer exploration of this until the Discussion section so that the results of the temperature analysis from EFUS can be considered alongside the results from this energy signature analysis.

Finally, the base EUI is fairly similar across the modelled scenarios, but shows a slight drop in the mean and median, and an increase in the spread for model 4. Model 4 incorporates the actual occupant number which would be expected to affect the base EUI significantly. The metered base EUI is similar to the modelled EUI for all scenarios (as expected since the total metered summer EUI was shown to be close to the modelled in the previous section), however the spread is much greater. This reflects that the SAP model is normative whereas actual energy use in homes is highly variable.

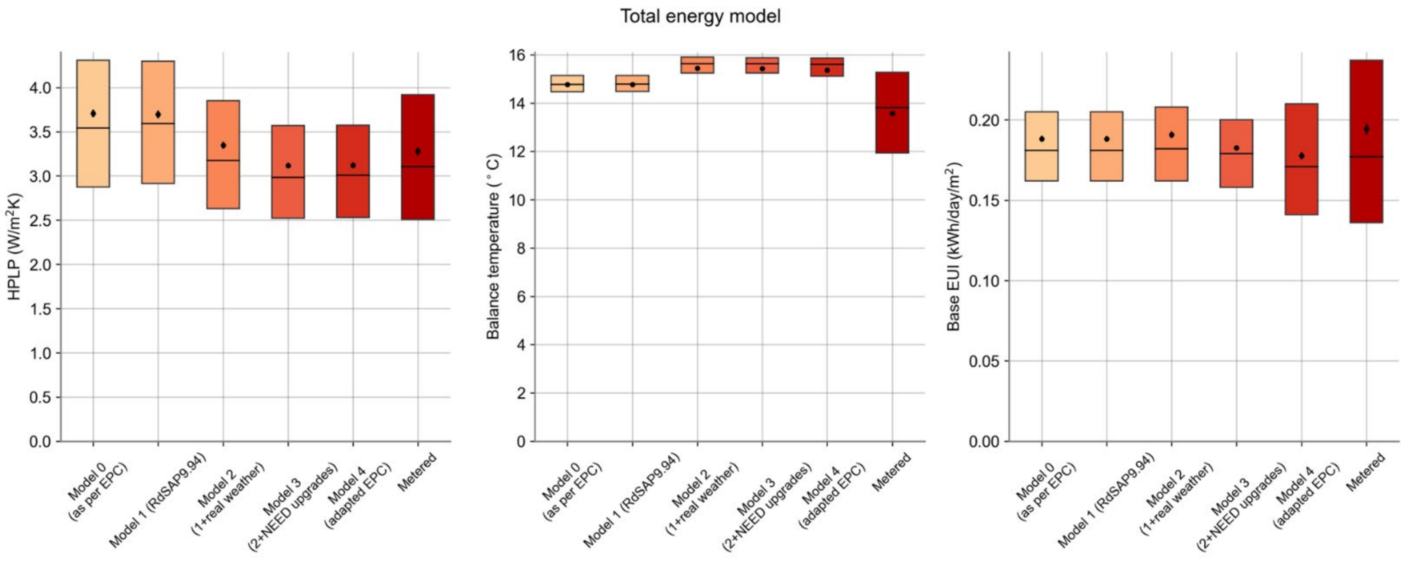


Figure 25 Distributions of PTG analysis parameters for the whole sample: HPLP, balance temperature and base EUI from left to right. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Energy signature analysis: contextual variable results

We have analysed the energy signature parameters by EPC band and by contextual variables which are particularly pertinent to the type of energy use described by the parameter. This section will first discuss the base EUI and HPLP broken down by EPC band, and then the HPLP by wall type, roof type, building age, and main heating system efficiency. We then present the base EUI broken down by occupancy, hot water system efficiency and hot water system type (combi or system boiler).

Figure 26 below shows how the total base energy use intensity varies by EPC band for each of the scenarios. Note that homes which would move EPC bands under different modelling scenarios, but remain classified under the original scenario EPC-band for this and the following analysis. The figure below shows that the total delivered energy in summer is reasonably well described by the model 0 to 2, but for less efficient EPC bands models 3 and 4 under predict total base EUI. This suggests that the expected reduction in summer energy use associated with the energy efficiency measures captured by NEED is likely to be an overestimate.

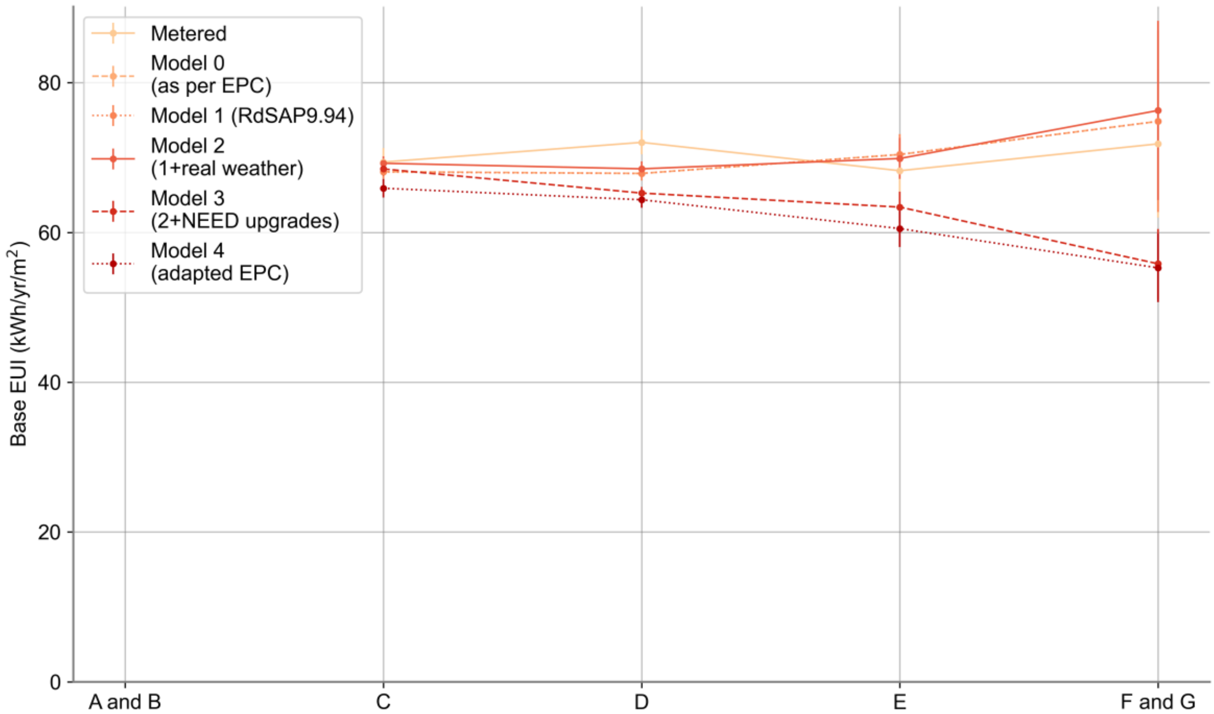


Figure 26 Average total baseline EUI (summer EUI) for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively.

Figure 27 and Figure 28 below show the gas and electricity base energy use intensity respectively. These figures show that the metered summer gas use is higher than modelled, while the metered electricity use is lower than modelled. The electricity base EUI shows a consistent difference between metered and modelled energy use of approximately 8 kWh/m²/yr across all EPC bands. Meanwhile, gas use shows variable results for different modelling scenarios. For scenarios 0 to 2 the gap reduces from more efficient to less efficient bands, meanwhile models 3 and 4 show an increasing gap moving from less efficient to more efficient bands. This suggests that some of the energy efficiency improvements in NEED are optimistically modelled and do not provide the level of energy savings expected.

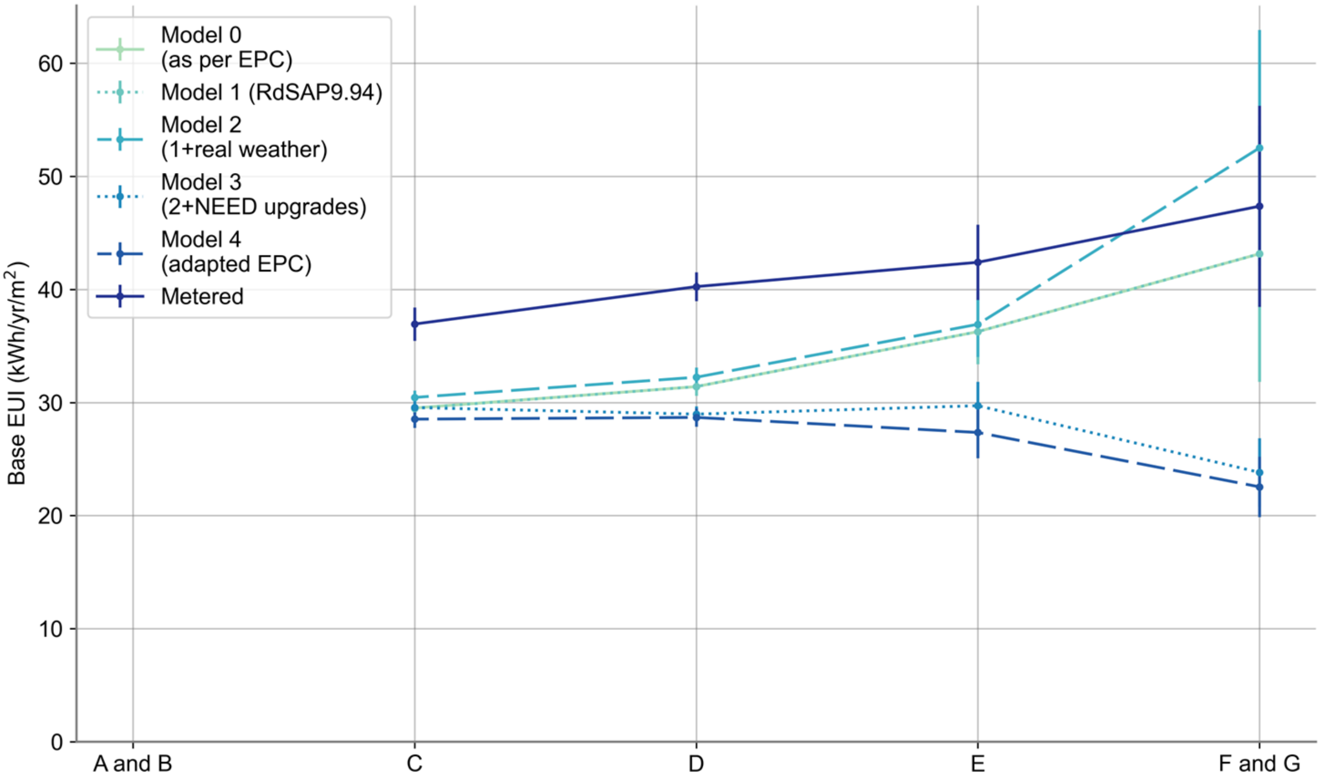


Figure 27 Average gas baseline EUI (summer EUI) for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively.

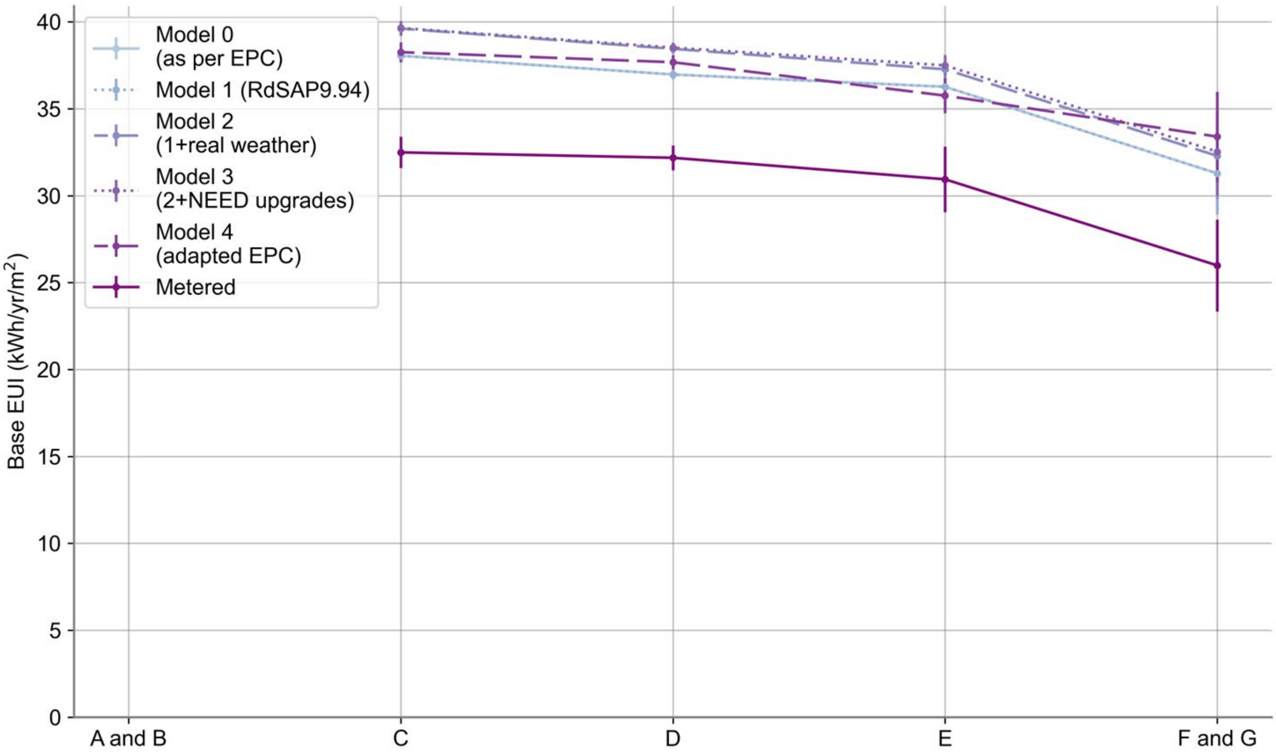


Figure 28 Average electricity baseline EUI (summer EUI) for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively.

Figure 29 below shows the metered and modelled HPLP for different EPC bands under different modelling scenarios. The metered HPLP shows a much shallower increase across EPC bands than the modelled values. Models 0 to 2 in particular show a very steep increase in HPLP across EPC bands. For model 3, which incorporates NEED energy efficiency upgrades, the modelled HPLP are reduced significantly compared to the previous models, with the decrease being largest in the most inefficient buildings. This reflects that the most inefficient buildings are likely to have been improved since the last EPC assessment was carried out. Homes in band C have higher modelled HPLP than metered for all models, meaning that these homes use a greater amount of energy for heating than is anticipated and suggesting that the more efficient homes may be optimistically modelled.

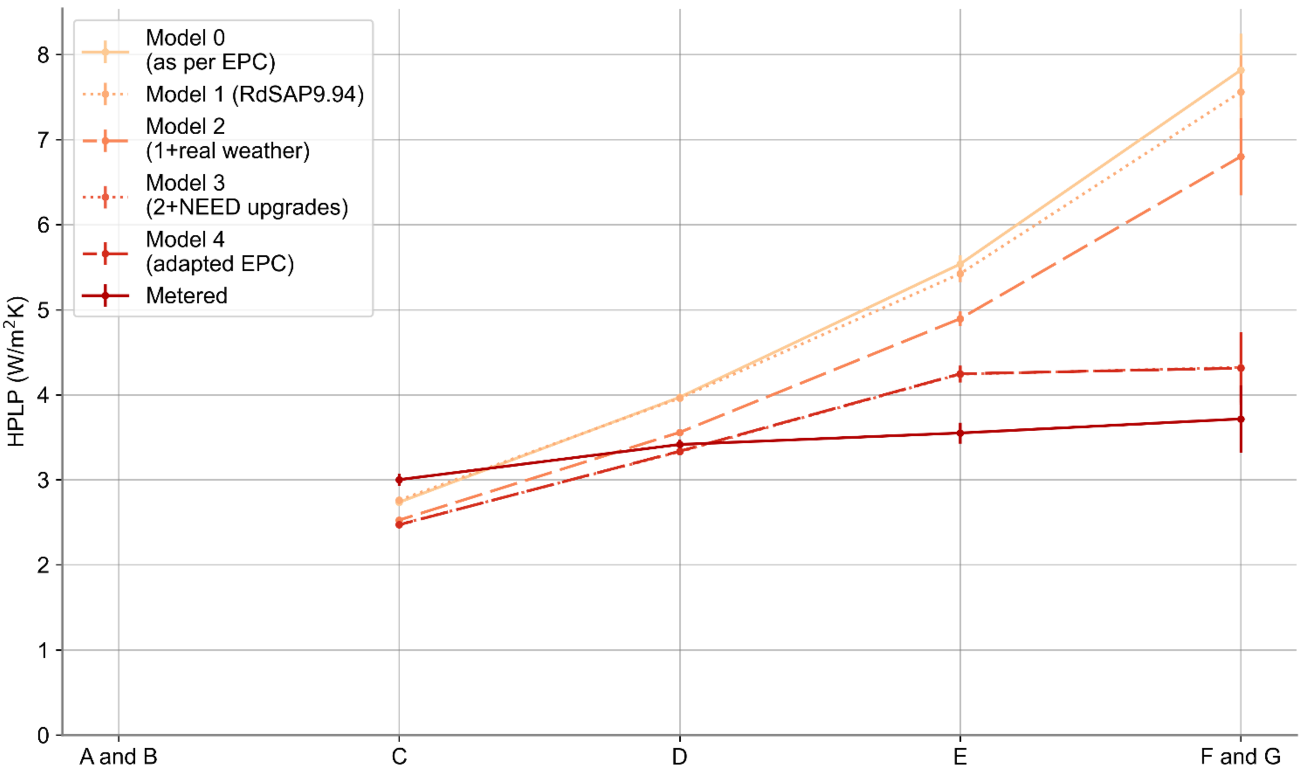


Figure 29 Average HPLP for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively. Note that model 3 and model 4 are extremely similar so difficult to distinguish.

Figure 30 below shows the distribution of HPLP for homes with different wall types as metered and under models 0 and 4. For model 0, on average all wall types show a greater modelled HPLP than metered. This difference is greatest for the least efficient wall type (solid walls) and reduces for more efficient wall types. The difference is greatly reduced for model 4, this is likely associated with the changes in default wall U-values introduced in RdSAP9.94, and the energy efficiency measured recorded by NEED. For model 4, the HPLP reduces moving from the least efficient to most efficient wall types, but the average modelled HPLP drops below the metered HPLP for homes with filled cavities and cavity insulation as built. This suggests that the performance of these wall types may in some cases be overestimated. Moreover, the metered HPLP for unfilled cavity walls is very similar to filled cavity walls. This could suggest that either many homes that are recorded as having unfilled cavities have filled cavities in practice, or that retrofit filled cavities do not perform as well as expected (or both).

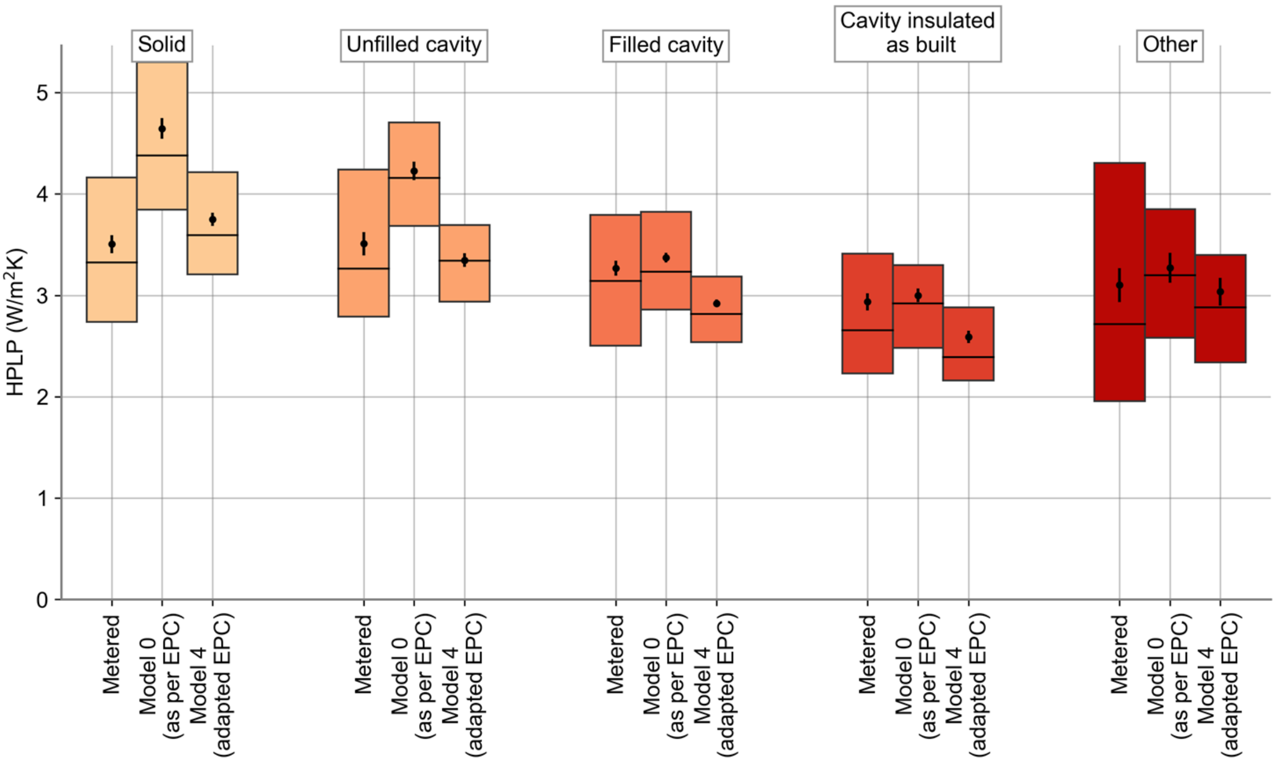


Figure 30 Distributions of HPLP for different wall types. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 31 below shows the distribution of HPLP for homes with different roof types as metered and under models 0 and 4. Similar to the analysis split by wall type above, the gap between metered and model 0 generally decreases from the least efficient to most efficient roof types. In particular, the difference between HPLP as metered and under model 0 for pitched roofs with no insulation is very large suggesting that many of these homes likely have some roof insulation even though the EPC does not record this. Additionally, the difference in metered HPLP is very small across all groups, again suggesting that many of the homes which have no or low levels of loft insulation recorded likely do have insulation in practice, typically when loft insulation levels are above 100mm it is not the primary driver of the difference in overall thermal performance between groups of homes but one of several important factors. The difference is reduced for model 4, reflecting that many of the homes have had energy efficiency retrofits, although as noted in the Methods section, the vast majority of retrofits were improvements to the heating system, with only 21 being improvements to loft insulation. As a result the difference between model 0 and model 4 is generally not associated with the loft insulation depth.

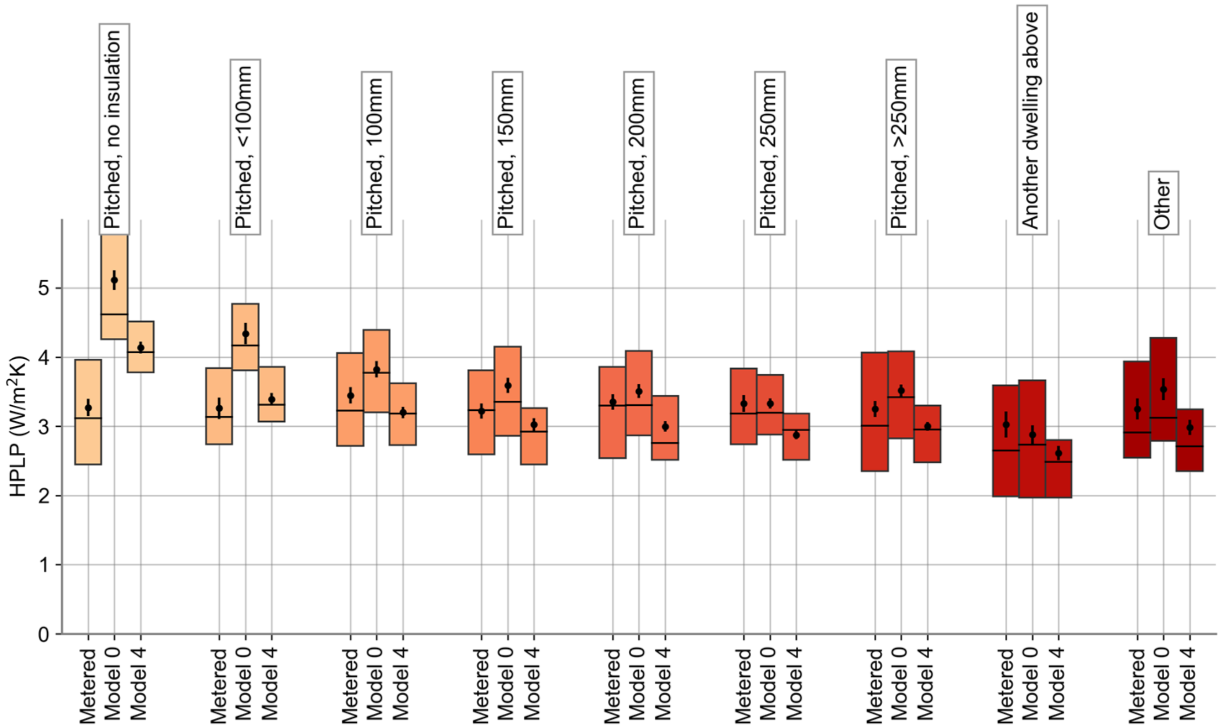


Figure 31 Distributions of HPLP for different roof types. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 32 below shows the distribution of HPLP for homes of different construction ages as metered and under models 0 and 4. Generally, the gap between metered and modelled HPLP is largest for the oldest buildings and decreases for the newest buildings. For model 4, the mean and median HPLP is smaller for the modelled than the metered HPLP from 1950 onwards, suggesting poorer performance for the homes that are expected to have better performance.

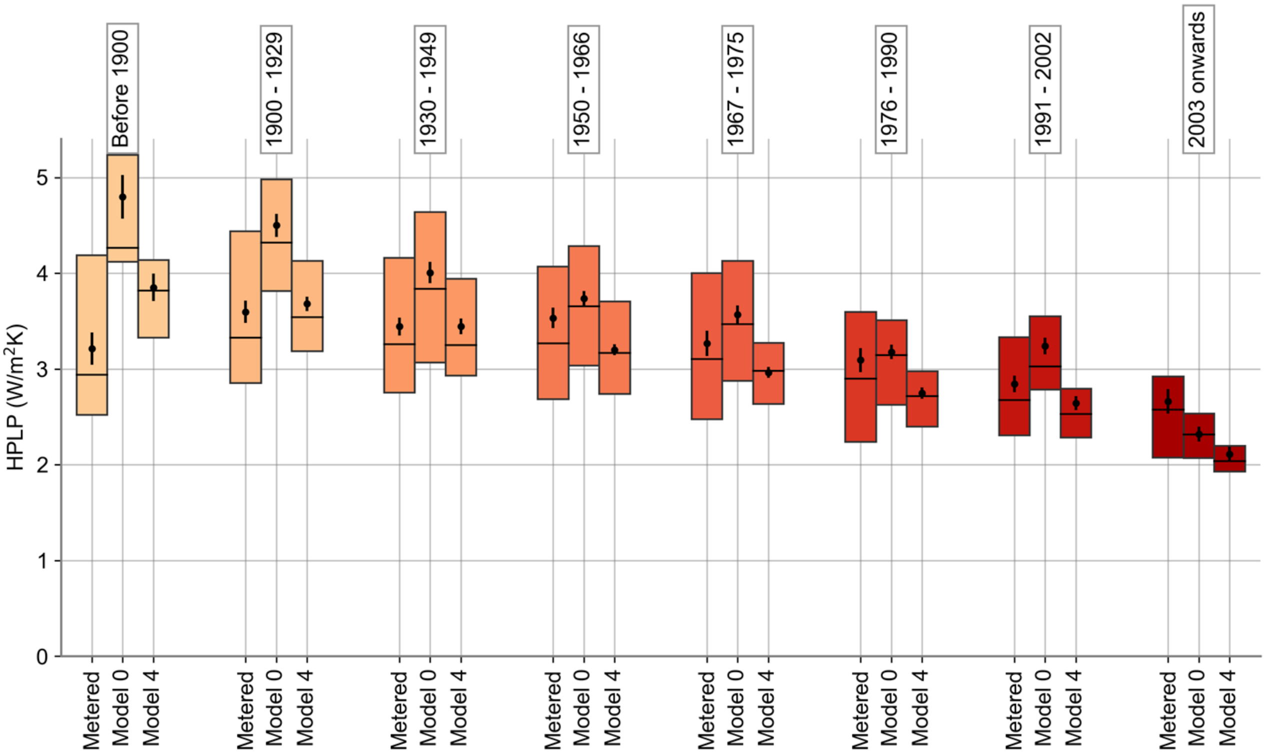


Figure 32 Distributions of HPLP for different building ages. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 33 below shows the distribution of HPLP for homes with different main heating system efficiencies as metered and under models 0 and 4. Homes with the least efficient heating systems have a very large gap when modelled under scenario 0, but this gap is much reduced for scenario 4. This suggests that many of the homes for which the EPC records a very inefficient heating system may have had a new, more efficient, heating system installed since the EPC was generated.

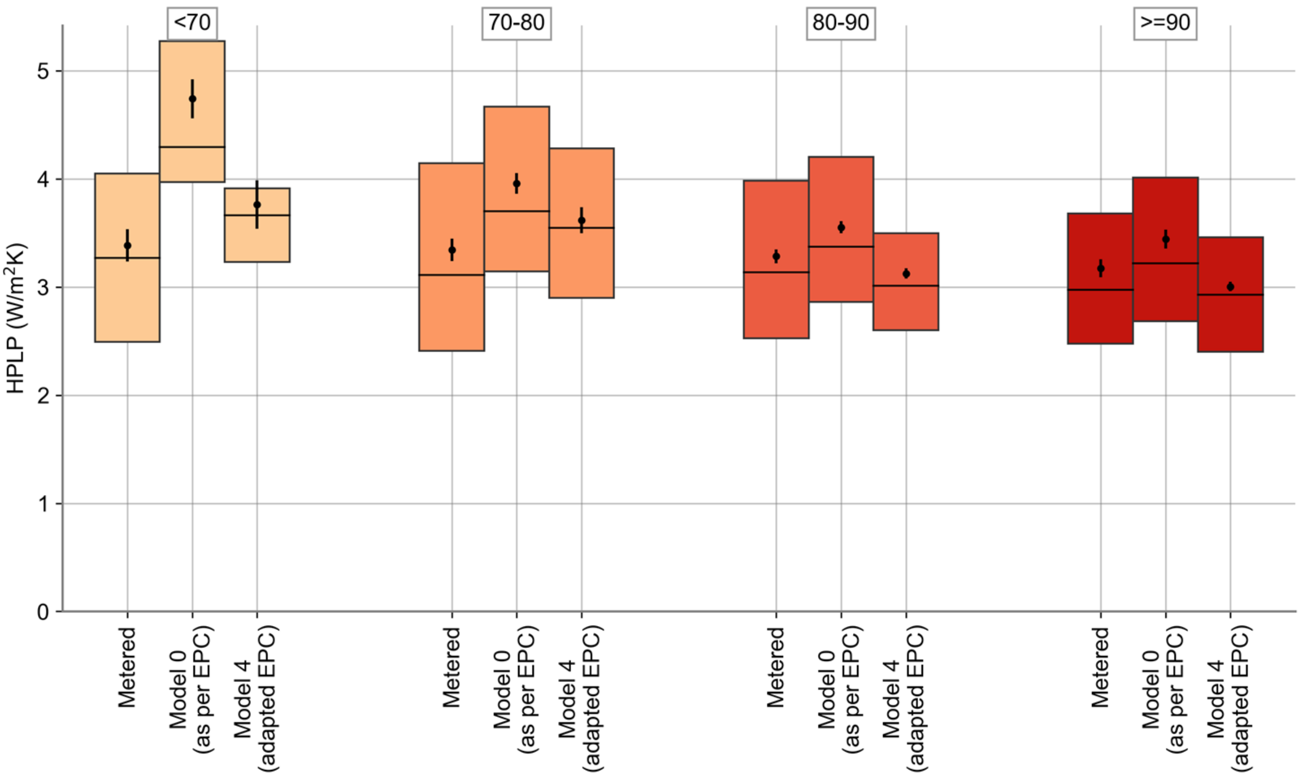


Figure 33 Distributions of HPLP for different heating system efficiencies. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 34 Distributions of HPLP according to the improvement in heating system energy efficiency. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point. below shows the distribution of HPLP for groups of homes which did, and did not, have the heating system efficiency upgraded between the original EPC and the year of metered data (2021). This shows that the homes which were upgraded had a difference in metered and model-0 HPLP of -0.7 W/m²K. The direction of this gap reverses for model 4, and decreases to 0.3 W/m²K suggesting that the improvement in efficiency associated with the heating system upgrade may be overstated. Note that the vast majority of energy efficiency upgrades modelled under scenario 3 were for heating and hot water system efficiency improvements (237 heating efficiency improvement compared to 48 fabric efficiency improvements).

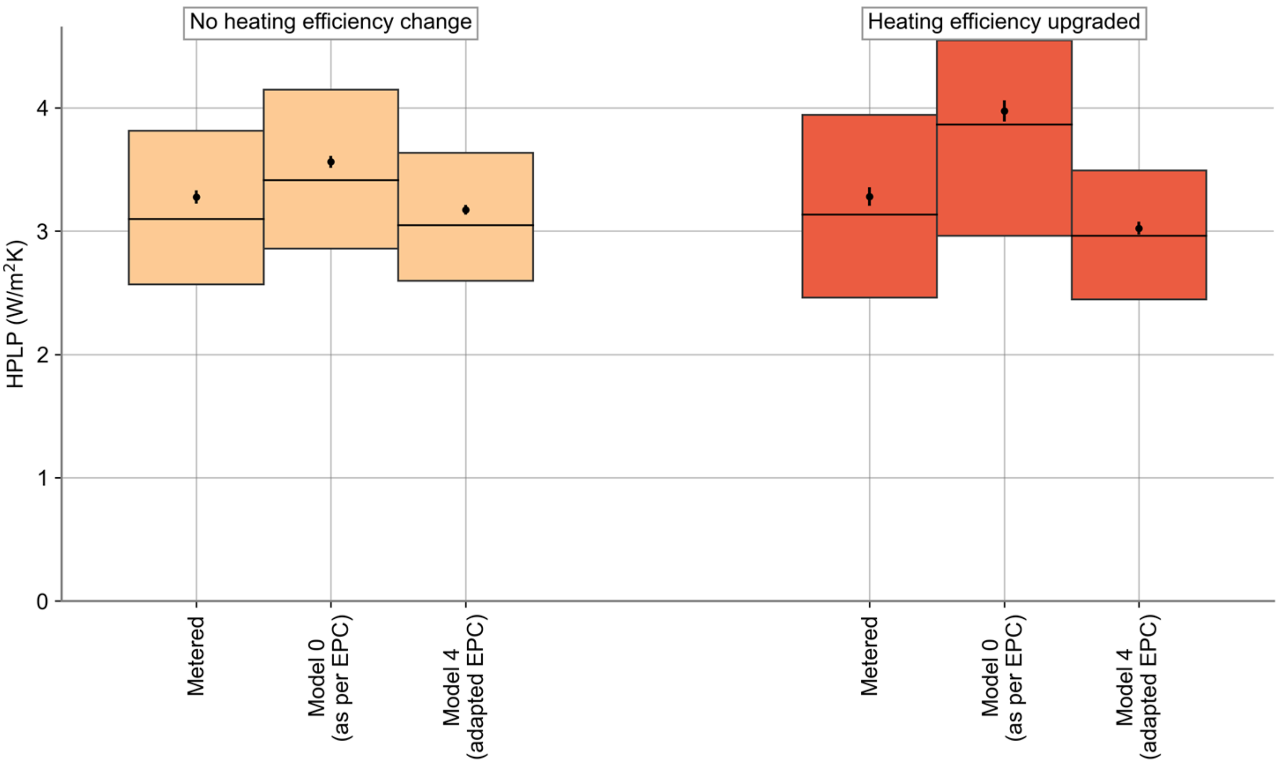


Figure 34 Distributions of HPLP according to the improvement in heating system energy efficiency. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 35 shows the distribution of HPLP for homes with different EPC transaction types as metered and under models 0 and 4. Notably homes that were rated for ECO or the green deal have a much higher HPLP when modelled under scenario 0, and this is much reduced for model 4. This is likely because these homes are very likely to have received an energy efficiency measure following the EPC assessment, and this is likely to have been lodged in NEED since assessment for one of these schemes indicates that the work is likely to have been recorded in a central database. The model 0 HPLP for the ECO and green deal homes are larger on average than the rest of the sample, this could be because these homes are particularly poorly performing and so have been specifically targeted for these energy efficiency schemes. It is not possible from this analysis to determine whether there could have been any instances of exaggerating the poor performance of homes when they are being rated for ECO or green deal. Marketed sale and rental are by far the largest groups and these groups show very similar trends to the overall sample as expected. Note that the 'other group' is largely made up of homes where there is no recorded reason for the EPC, with a small number of RHI and stock condition surveys.

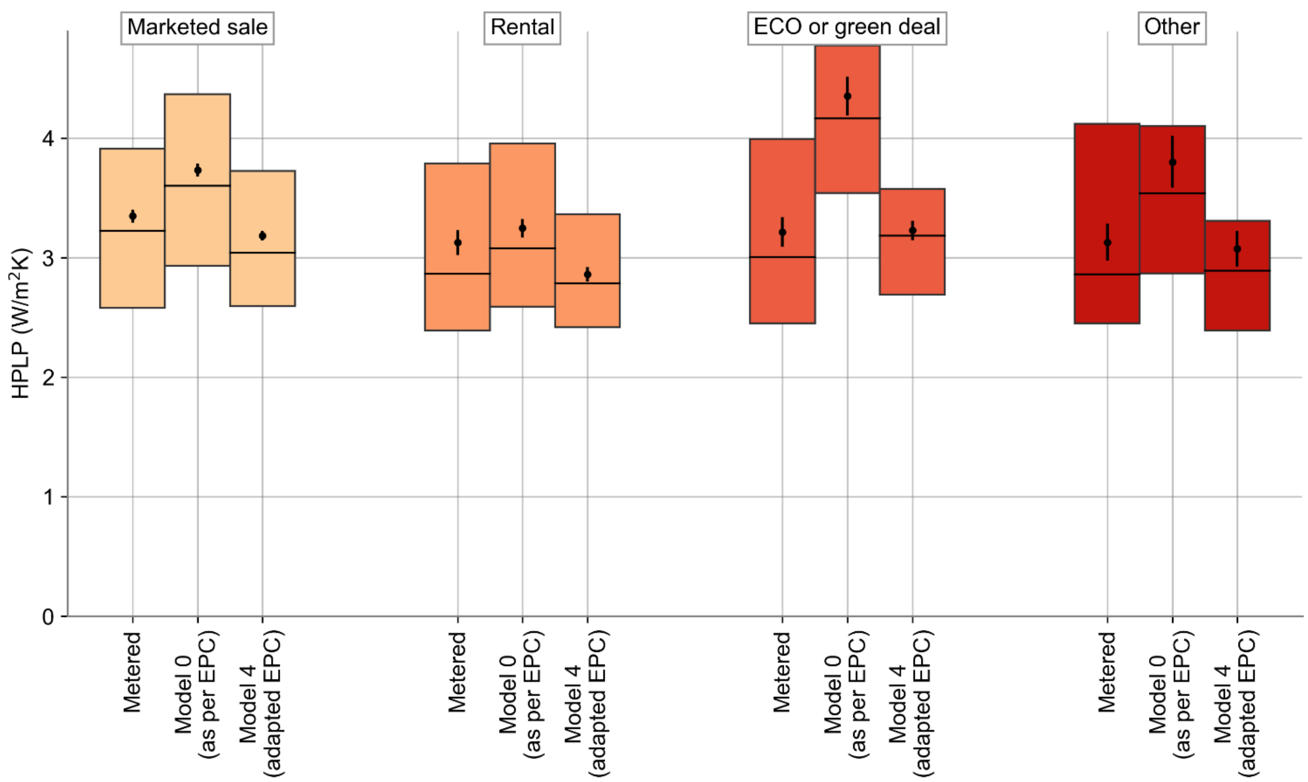


Figure 35 Distributions of HPLP for different EPC transaction types. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 36 shows the distribution of baseline EUI for homes with differing agreement with the SAP assumed number of occupants. For model 0, the metered baseline EUI matches the model for homes where the number of occupants is in agreement between the participant survey and the SAP assumptions. As expected, for homes where the survey reports a greater number of occupants than assumed by SAP the metered baseline EUI is greater than the model and vice versa for homes where the survey reports fewer occupants than is assumed by SAP, reflecting that the baseline energy use is driven by occupancy. For model 4, which corrects for the number of occupants according to the survey, shows similar baseline EUI for survey more than or equal to SAP, but the model has lower baseline EUI than metered for homes where the number of occupants according to the survey is less than assumed by SAP.

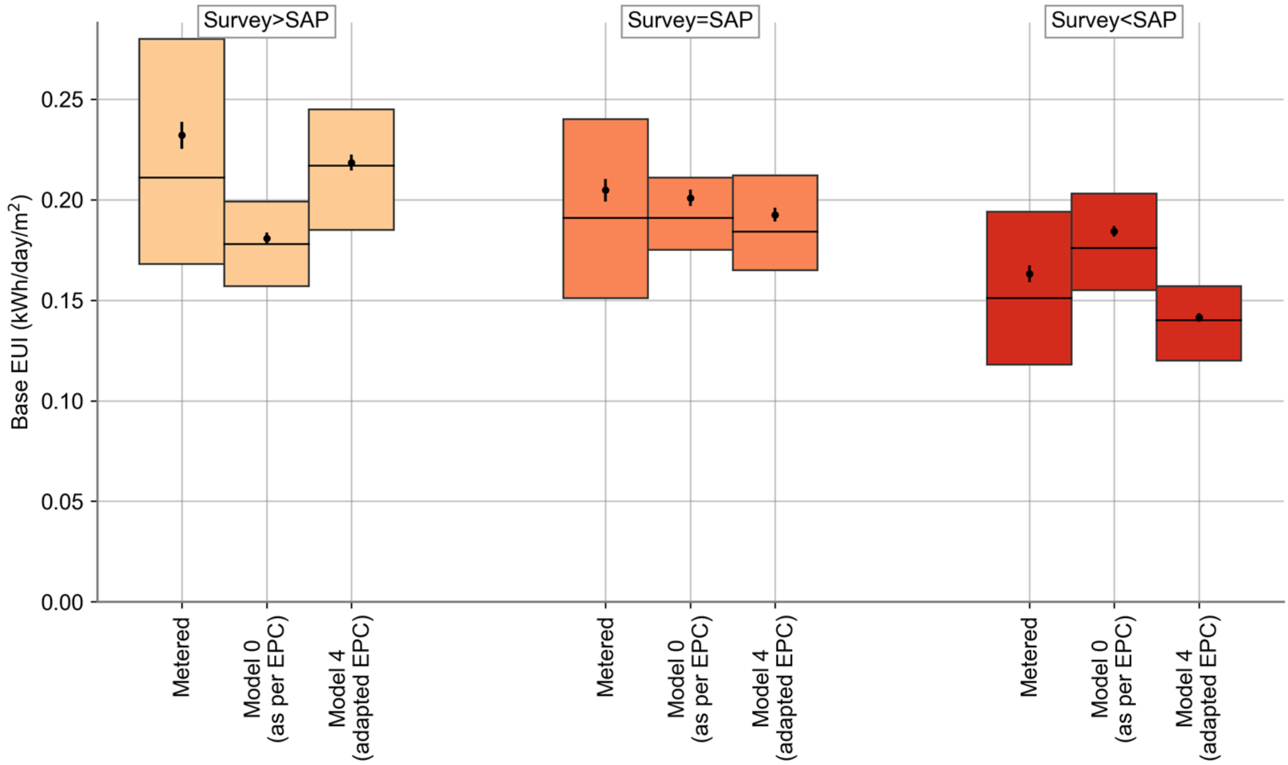


Figure 36 Distributions of baseline EUI split by agreement between the participant survey and SAP assumed occupant numbers. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 37 shows the distribution of baseline EUI for homes with different hot water system efficiency. Note that the >85% efficiency group is exclusively made up of condensing combi boilers, the 75% - 85% group is made up of condensing combi and condensing system boilers, and the 65% - 75% group is largely non-condensing combi and system boilers, with some condensing system boilers and a very small number of condensing combi boilers. Homes with the least efficient hot water systems have a much higher modelled baseline EUI for both models, although the difference is much greater for model 0. Meanwhile, homes with the most efficient hot water systems have very similar baseline EUI for both models, albeit with a much greater spread for model 4.

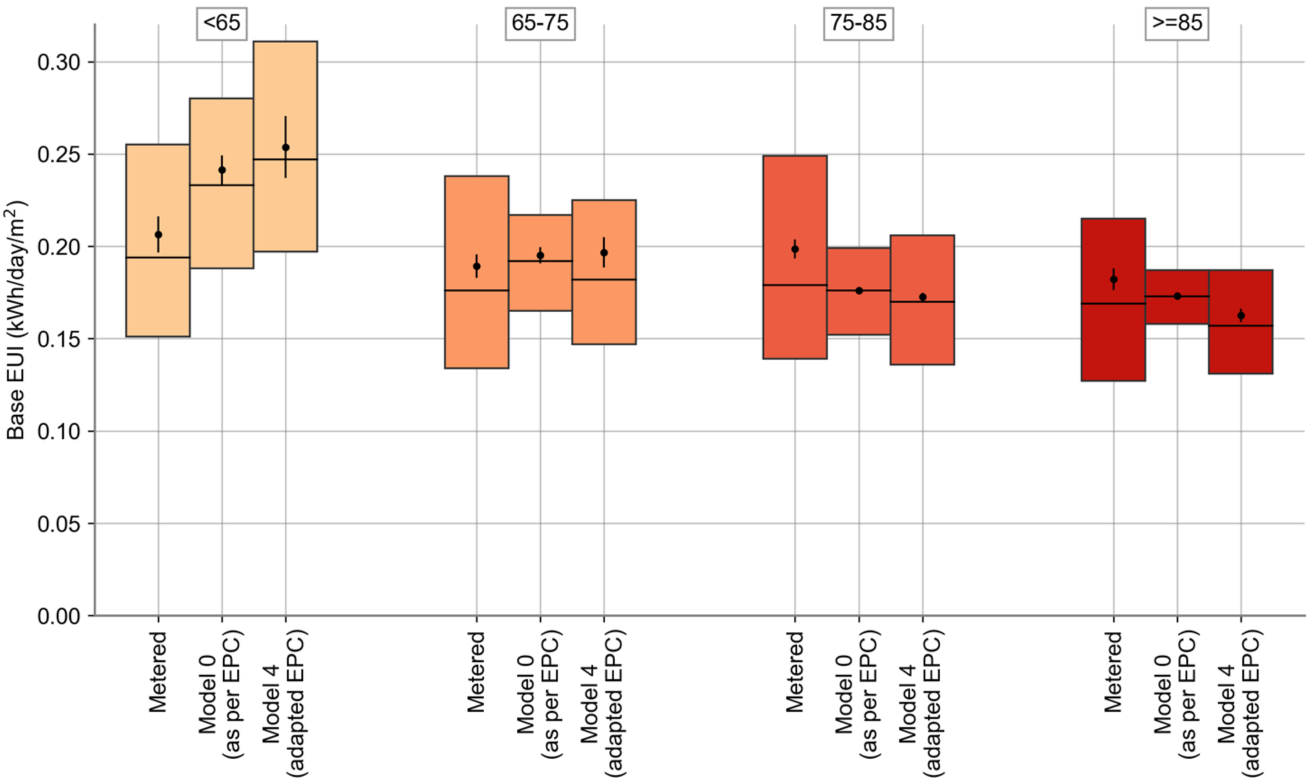


Figure 37 Distributions of baseline EUI for different water heating system efficiencies. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Figure 38 below shows the distribution of baseline EUI for homes with different hot water types. Homes with system boilers are modelled to have higher baseline EUI than metered under model 0, but the agreement is good for model 4. This likely reflects that many system boilers would have been replaced with combi-boilers in the time elapsed since the EPC was generated.

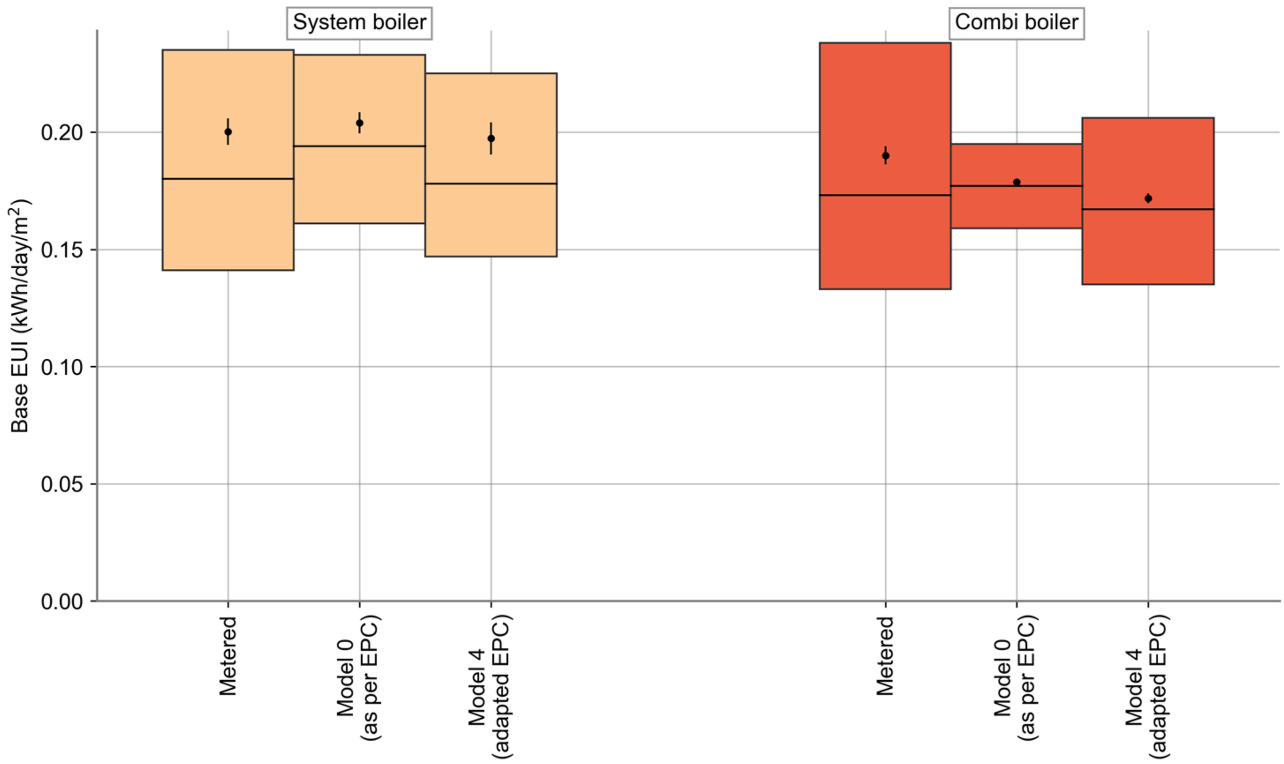


Figure 38 Distributions baseline EUI for different water heating system types. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

Regression analysis of performance gap

In this section we present the results of the regression analysis that was carried out to further investigate the parameters associated with the performance gap. We present the analysis using the annual energy use intensity here, and provide the results of regression analysis on the difference in HPLC and the baseline EUI in Appendix A.

Table 9 below summarises the goodness of fit indicators of the regression model for explaining the performance gap. The adjusted R^2 suggests that 29% of the variation in the difference between metered and modelled EUI can be explained by a linear model of the parameters included in this regression.

Table 9 Goodness of fit indicators for the linear regression of the energy performance gap for model 0.

Statistic	Value
Mean absolute error (MAE)	42.0
Root mean square error (RMSE)	54.9
R^2	0.33
Adjusted R^2	0.29

Table 10 below summarises the modelled coefficients and their statistical significance, note that a negative coefficient means that the parameter is associated with a greater overprediction of energy use by the model. Two of the wall types – cavity wall as built with no insulation assumed and solid walls with no insulation are significantly associated with a greater overprediction of energy use in the regression compared to the reference category of a filled cavity wall. None of the floor types are significantly associated with the performance gap compared to a solid floor with no insulation assumed. Compared to the reference category of pre-1900 buildings, only 1930-1949 buildings have a statistically significant coefficient, with these buildings being associated with a reduced performance gap. Three of the roof types are significant compared to the reference category of a pitched roof with more than 250 mm of insulation: no insulation, less than 100 mm, and 100mm of loft insulation. All three of these categories are associated with an increasing gap, and the size of the effect increases with decreasing levels of insulation as expected. Homes that are struggling financially are associated with an increasing performance gap compared to those that are comfortable. Homes that have a system boiler are associated with an increasing performance gap compared to those that have a combi boiler. Having a greater number of occupants assumed by SAP is associated with an increased performance gap. A larger thermostat set point compared to SAP is associated with a reduced performance gap, although by a relatively small amount per ^{o}C of difference. A greater proportion of secondary heating is associated with a larger performance gap, note that although the coefficient for this parameter appears large, the variable is expressed as a proportion, and this is typically less than 0.1.

The direction of the coefficients that are statistically significant are as expected, although some parameters which might be expected to be significant are not. For example, it is perhaps surprising that so few building ages are statistically significant. However, it should be noted that building age interacts with other parameters in a non-trivial way in the SAP model, for example building age and wall type combine to give an assumed wall value in RdSAP. The structure of the model does not take this into account, largely because sample sizes become extremely small for groups of homes within given building ages and wall types, meaning that results are unlikely to be statistically significant.

Table 10 Coefficients and p-values of variables in the linear regression of the performance gap

Variable	Coefficient	P-value
Intercept	-17.2	0.240
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, insulated	9.1	0.353
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, no insulation	**-26.0**	**0.000**
Wall type. Reference: cavity wall, filled cavity; treatment: other	-13.3	0.146
Wall type. Reference: cavity wall, filled cavity; treatment: solid brick, as built, no insulation	**-25.8**	**0.004**
Floor type. Reference: solid, no insulation (assumed); treatment: another dwelling below	1.8	0.853
Floor type. Reference: solid, no insulation (assumed); treatment: other	-15.6	0.467
Floor type. Reference: solid, no insulation (assumed); treatment: solid, insulated	17.0	0.172
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, insulated	9.8	0.514
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, no insulation (assumed)	7.3	0.225
Dwelling age. Reference: pre-1900; treatment: 1900- 1929	10.8	0.387
Dwelling age. Reference: pre-1900; treatment: 1930- 1949	**25.7**	**0.045**
Dwelling age. Reference: pre-1900; treatment: 1950- 1966	9.9	0.470
Dwelling age. Reference: pre-1900; treatment: 1967- 1975	-2.8	0.844
Dwelling age. Reference: pre-1900; treatment: 1976-1990	23.6	0.110
Dwelling age. Reference: pre-1900; treatment: 1991-2002	2.2	0.898
Dwelling age. Reference: pre-1900; treatment: 2003 onwards	24.5	0.195
Roof type. Reference: pitched, more than 250mm; treatment: another dwelling above	-9.1	0.396
Roof type. Reference: pitched, more than 250mm; treatment: other	-5.7	0.545
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 100 mm loft insulation	**-17.3**	**0.041**
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 150 mm loft insulation	-7.6	0.379
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 200 mm loft insulation	15.8	0.078
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 250 mm loft insulation	14.1	0.120
Roof type. Reference: pitched, more than 250mm; treatment: pitched, less than 100mm loft insulation	**-27.7**	**0.009**
Roof type. Reference: pitched, more than 250mm; treatment: pitched, no insulation (assumed)	**-47.7**	**0.000**
Unheated spaces. Reference: all space heated; treatment: has unheated space or no answer	-6.6	0.224
Managing financially. Reference: comfortable; treatment: struggling or no answer	**-13.4**	**0.019**
Hot water system. Reference: combi boiler; treatment: system boiler	**-20.1**	**0.000**
SAP occupants – survey occupants	**-15.7**	**0.000**
Survey thermostat set point – 21°C	**5.5**	**0.000**
Proportion of total energy use attributed to secondary heating	**-192.7**	**0.000**

The regression analysis carried above was completed using model scenario 0 (EPC as-found), however, further work presented in Appendix A shows how the results differ under scenario 4. Compared to the results for model 0, we see that none of the wall types are now significant, suggesting that the updates to U-values carried out in the most recent versions of RdSAP have improved the modelling of this parameter. None of the building ages are significant, although as noted for scenario 0, the building age influences several other parameters non-directly and the structure of this model does not take this into account. Two roof types are significant in the current results, the group which are recorded as having no insulation and the group with another dwelling above. This suggests that it is likely that many homes which are recorded as having no loft insulation do actually have loft insulation, and that homes with another dwelling above perform better than expected. The proportion of secondary heating remains significant, although it is worth noting that the proportion is always less than 10%, so the effect is at maximum similar to that for homes with another dwelling above.

SAP modelled Mean Internal Temperature (MIT) compared to metered MIT with both EER banding and HLP

This section presents the results of analysis carried out on the EFUS Measured internal temperatures and the comparison to SAP-NBM Modelled internal temperatures.

Summary of temperatures

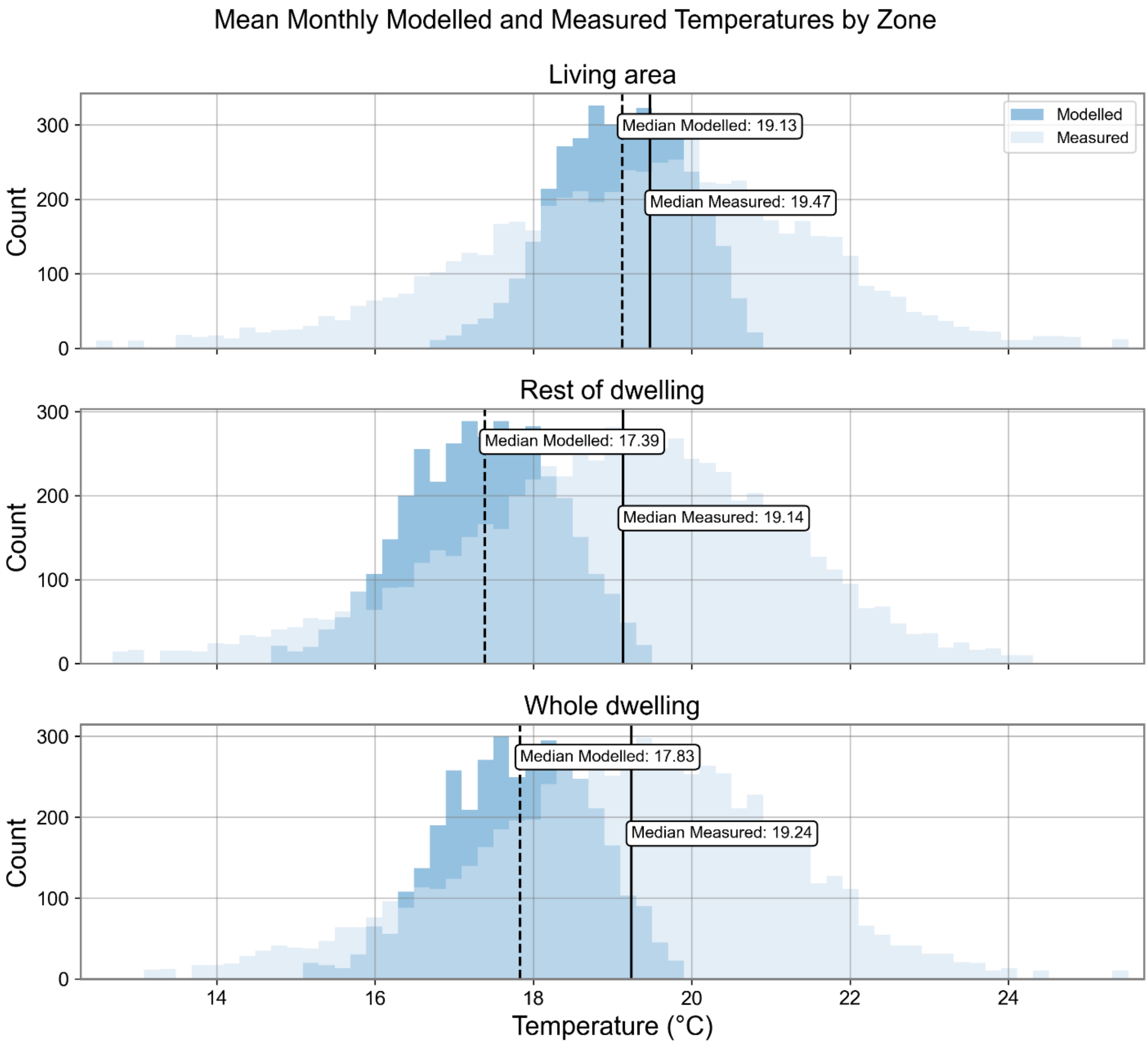


Figure 39 Histogram comparing Mean Monthly Internal Temperatures for Modelled and Measured data for the heating season. Bins with fewer than 10 data points are excluded.

Figure 39 shows the distribution of Mean Monthly Modelled and Measured internal temperatures during the heating season for the same gas heated dwellings in both the modelled and measured data. The median SAP rating in the population is 65 (band D).

This figure shows a clear disparity in the distributional characteristics between modelled and measured data, with the central tendency of the measured data being between 19°C and 19.5°C for each of the zones modelled by SAP-NBM, and the modelled data being consistently cooler. This is especially pronounced in the two zones that SAP-NBM assumes to be heated to a lower temperature. In fact, the Measured data suggests that there is little difference in temperature between the Living Area (Z1), the Rest of the Dwelling (Z2) and the Whole dwelling, whereas the Modelled data suggests close to 2°C reduction between Z1 and Z2.

Linear Regressions

To investigate the relationship between internal temperature and SAP rating, and to fairly compare measured to modelled results, linear regressions were performed on mean monthly heating season temperatures for both measured and modelled data, and used to predict internal temperatures at an external temperature of 7°C. Linear models are simple and interpretable, and are suited to understanding broad trends in large data sets such as this one.

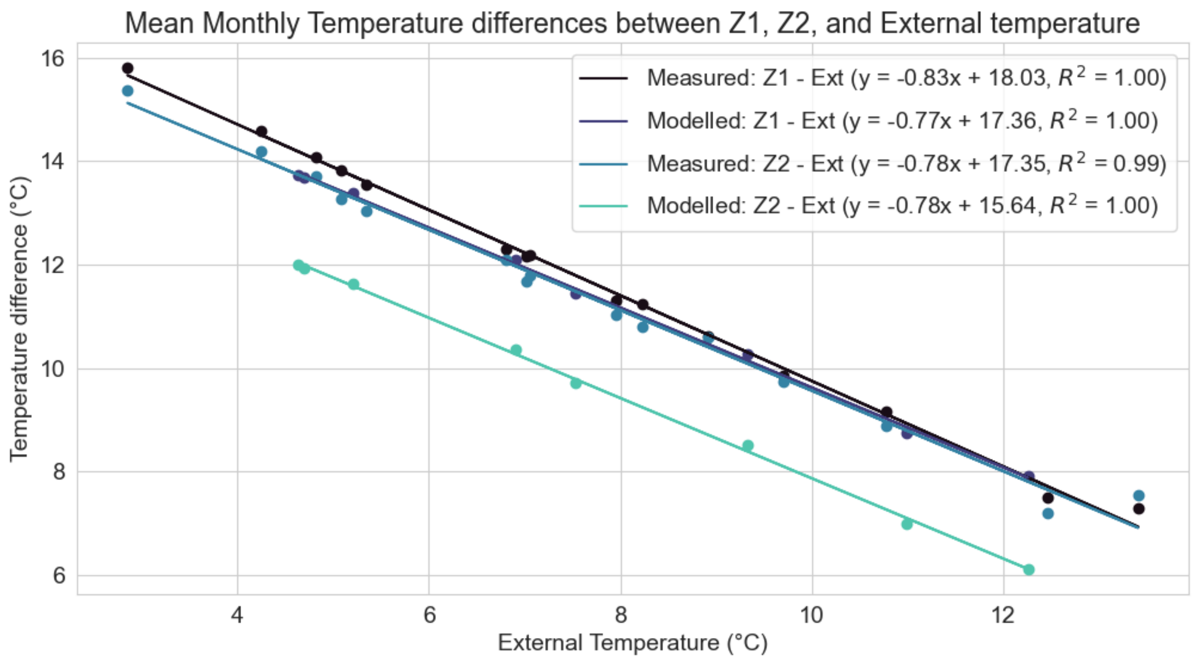


Figure 40 Linear regression for mean monthly temperature difference between indoors and outdoors versus external temperature for modelled and measured data during the heating season.

A slightly different approach to aggregation of the temperature data is to aggregate not on an individual dwelling level, but to aggregate on the different zones across all dwellings. Figure 40 shows the relationship between the difference between Mean Monthly External Temperature and the Mean Monthly Internal Temperature, and the External Temperature for Z1 and Z2, for both Modelled and Measured data.

Here, it is clearly demonstrated that the difference in temperature between Zone 1 and Zone 2 is consistently overestimated by the model. Together, these figures suggest that the two-zone model within SAP is not supported by empirical evidence. Furthermore, this suggests that if measured data was used in the calculation of heat demand within SAP, this would lead to an overprediction, rather than the hypothesised underprediction, of energy use.

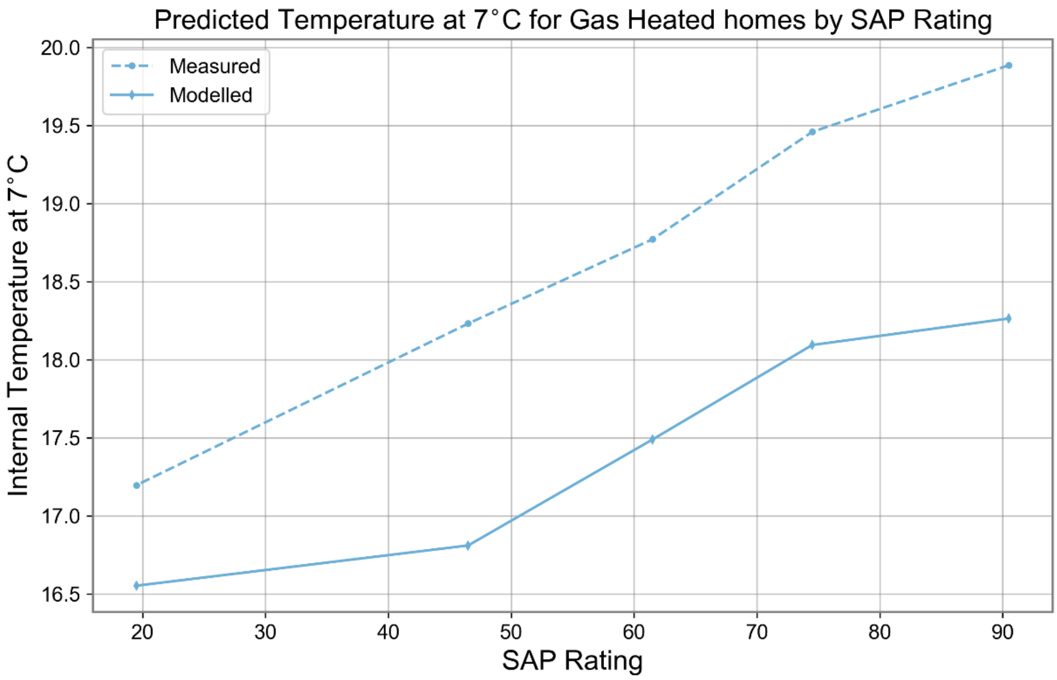


Figure 41 Predicted Indoor temperatures for an external temperature of 7°C, verses SAP rating for measured and modelled monthly data for the heating season, predicted on the basis of a linear regression.

Figure 41 shows a large (approximately 2.5°C) difference in temperature between the most and least efficient properties. Interestingly, the measured data shows a greater difference in temperature between bands F&G and band E than the modelled data.

However, if the performance gap could be explained by underheating of inefficient dwellings, we would expect to see measured temperatures being lower than modelled for these inefficient properties. Instead, although it is true that the measured data shows that the least efficient properties are almost 2.5°C cooler than the most efficient, they are still almost 1°C warmer than the modelled data predicts. Again, this figure suggests that using real temperature data within SAP would extend, rather than shrink, the performance gap, although how the gap changes with EPC band would change slightly.

Predicted Indoor Temperatures

Note that where comparisons are made between modelled and measured data in this section, Predicted Indoor Temperatures have been produced for the measured and NBM-SERL modelled data. These are predicted indoor temperatures for an external temperature of 7°C, on the basis of a linear regression on mean monthly temperatures for the heating season. There is therefore a single predicted temperature for each dwelling, extrapolated from modelled and measured data. This ensures a fair comparison between modelled and measured data, with the effect of external temperature minimised.

Figure 42 shows the Measured whole dwelling predicted temperature for the 462 gas heated homes, compared with available self-reported thermostat data. Note that bins with fewer than 10 data points are excluded to comply with SDC (statistical disclosure control) best practice. It is to be expected that the overall mean predicted temperature is less than the demand temperature due to the intermittency of heating use. Within modelled data, the demand temperature is set to 21°C for the living area, however, respondents to the EHS for the subsample of homes with measured temperature data report a median thermostat setting of 20°C. Although dwellings are slightly warmer than modelled therefore, thermostat settings are lower. This suggests that on average, buildings are making better use of heat than modelled data suggests.

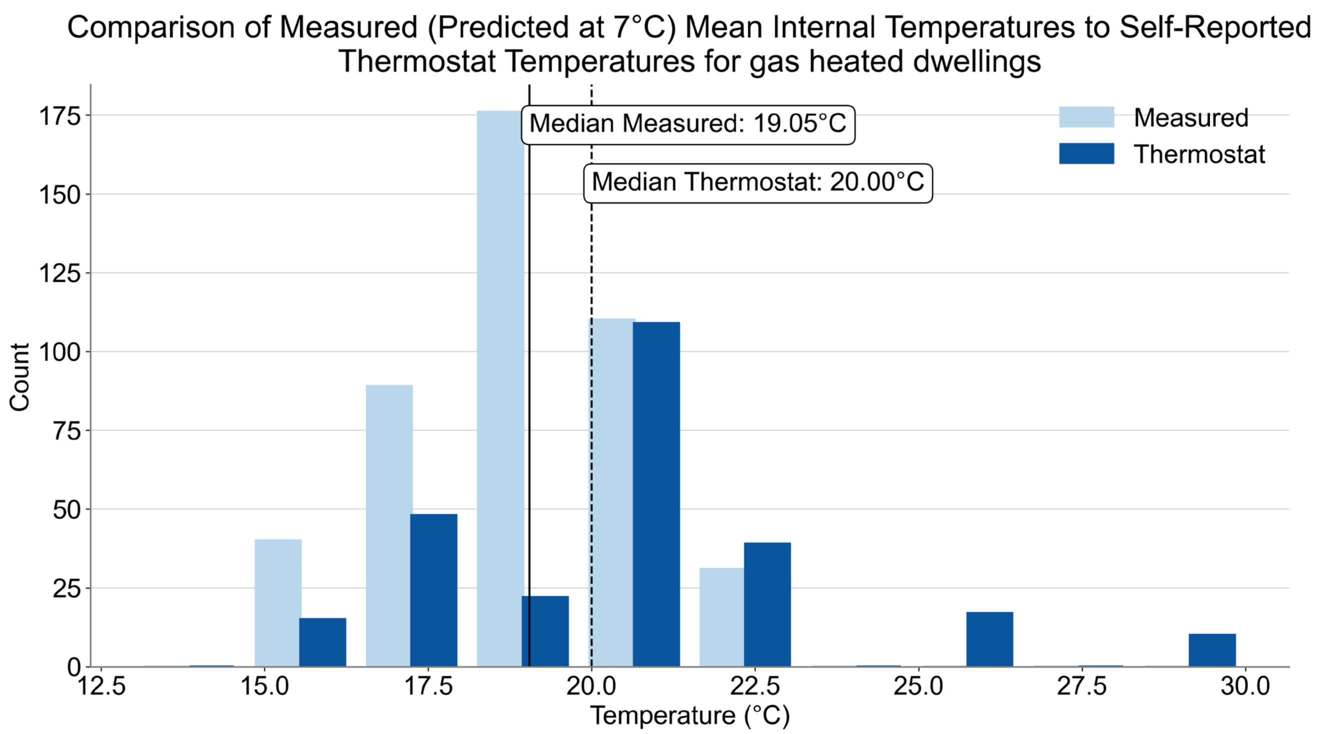


Figure 42 Histogram of Predicted Temperatures for the whole dwelling with available data for thermostat settings.

Figure 42 shows that the median whole dwelling predicted temperature for gas heated homes in the measured data is 19.05°C. This is close to the daytime Standardised Indoor Temperatures (SIT)[56] of 19.1°C calculated by Oreszczyn et al., (2006) for dwellings in receipt of energy efficiency upgrades as part of the Warm Front scheme.

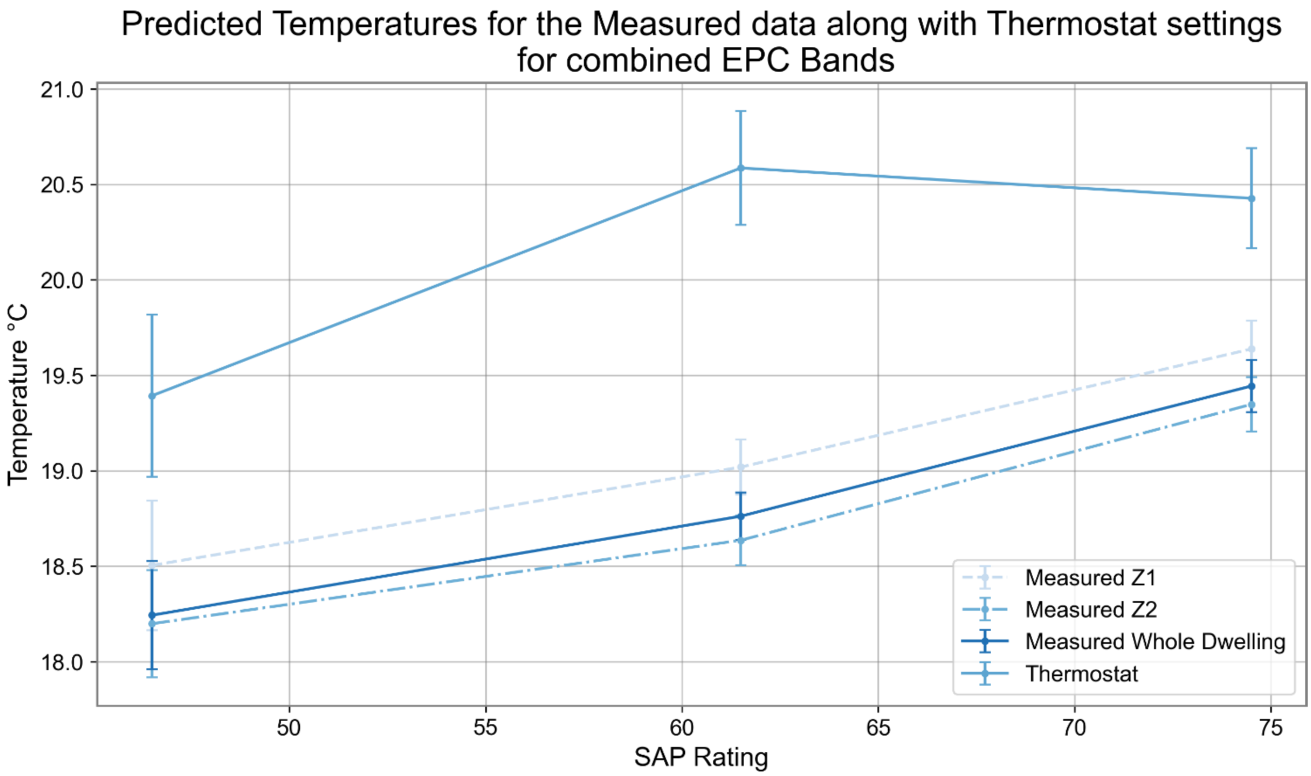


Figure 43 Plot showing the mean Predicted Indoor Temperatures for the Living area (Z1), Rest of Dwelling (Z2) and Whole Dwelling, for bands C to E, with error bars representing the standard error on the mean.

Figure 43 shows that as expected, the least efficient properties are the coolest, and that although there seems to be a small temperature difference between Zone 1 and Zone 2 for each band, this is a much smaller effect than modelled data shown in Figure 39 suggests.

56 Standardised Indoor Temperatures (SITs) show the indoor temperature predicted using a quadratic regression of internal against external temperature for each dwelling, for an external temperature of 7°C

Heating System Controls (Main heating system)

Heating system controls influence modelled temperatures in complicated ways, and how the system is controlled is assumed to influence the amount of heat energy consumed by the dwelling, with better controls assumed to reduce the overall demand temperature, through both zonal control and shorter heating periods[57]. Table 4e in SAP 2012 groups different main heating systems into three control categories, with the control group 1 consisting of systems with no timer or thermostatic control, or having a programmer but no room thermostat and vice versa, or only a room thermostat. This group accounts for 15% of dwellings. Control category 2 accounts for 82% of dwellings and represents systems that have programmers and at least two thermostats, or combinations of programmers, thermostats, and thermostatic radiator valves (TRVs). Lastly, control category 3 is described as having both time and temperature control, by 'suitable arrangement of plumbing and electrical services'. This is intended to provide the most control, however only a minority (2%) of dwellings present in this database are allocated to this group.

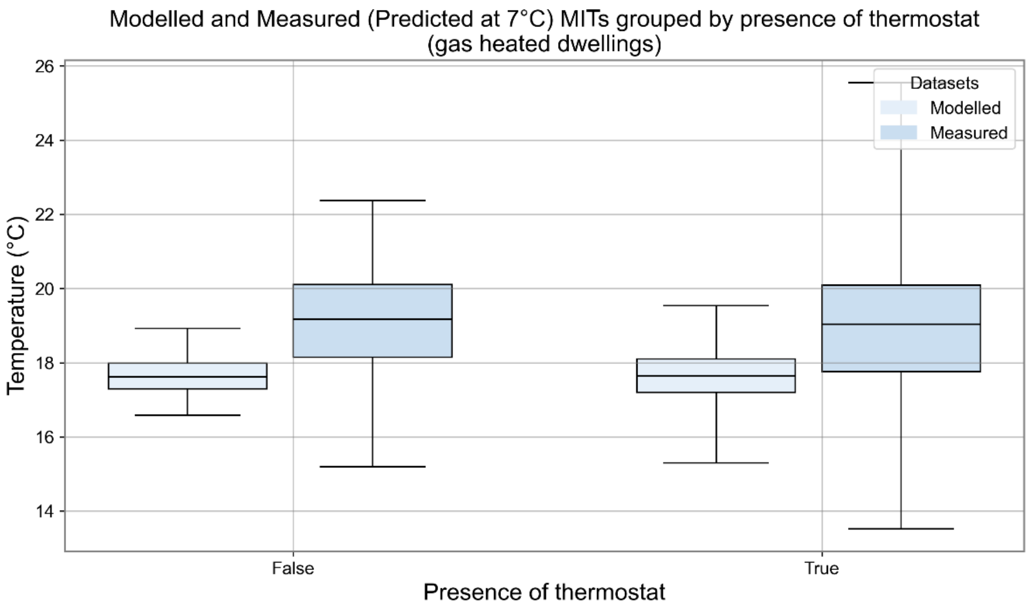


Figure 44: Box plot showing the Modelled and Measured predicted temperatures, disaggregated by presence of thermostat.

Figure 44 is a box plot showing the characteristics of Modelled temperatures compared to Measured Predicted temperatures, disaggregated on the basis of there being a thermostat present or not. Note that only 10% of the dwellings in the measured data do not have a thermostat. Although the modelled is again cooler than measured, there is no evidence in this plot, for either the modelled or the measured data, to suggest that presence of thermostat impacts the mean internal temperature.

[57] For further discussion refer to Appendix J

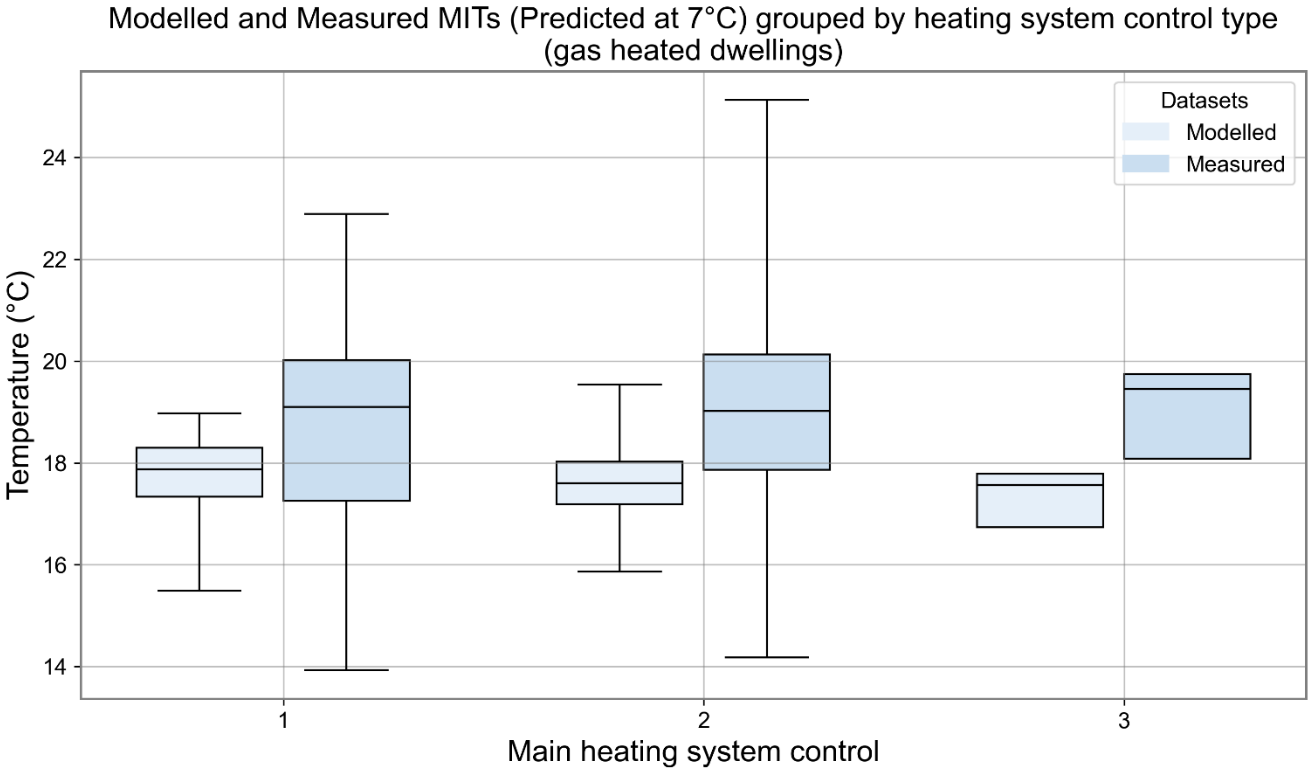


Figure 45 Predicted temperatures for the whole dwelling for modelled and measured data, disaggregated by heating system control code. Control group 1 : systems with no timer or thermostatic control or having a programmer but no room thermostat and vice versa, or only a room thermostat. Control category 2: programmers, thermostats, and thermostatic radiator valves (TRVs). Control category 3: both time and temperature control.

Figure 45 shows the distributional characteristics of the predicted internal temperatures for Modelled and Measured data for three control categories for the whole dwelling. Although the difference is small, the trend from least to most control for measured and modelled temperatures appears to be in opposite directions for the whole dwelling data.

This suggests that contrary to commonly held assumptions about SAP, the benefit of greater control is not associated with lower MITs. There are a variety of potential reasons for this that it would be valuable to investigate. First, occupants could be heating their dwellings more evenly and consistently in dwellings with newer control systems. Second, dwellings with better controls might be populated with more affluent occupants who can afford more heating, and third, these control categories might be associated with better, more efficient heating systems and buildings which are able to maintain higher temperatures[58].

[58] With thanks to Jason Palmer for his helpful commentary.

Dwelling Age

Within the SAP model there is a strong relationship between the thermal efficiency of the building and its age, because table S6 defines the U-values of walls depending on their (approximate) age band. It is therefore reasonable to expect that modelled temperatures are higher in newer properties that are assumed to be more efficient. If the relationship between age and wall U-value is correctly described in SAP, the same effect should be visible in the measured data.

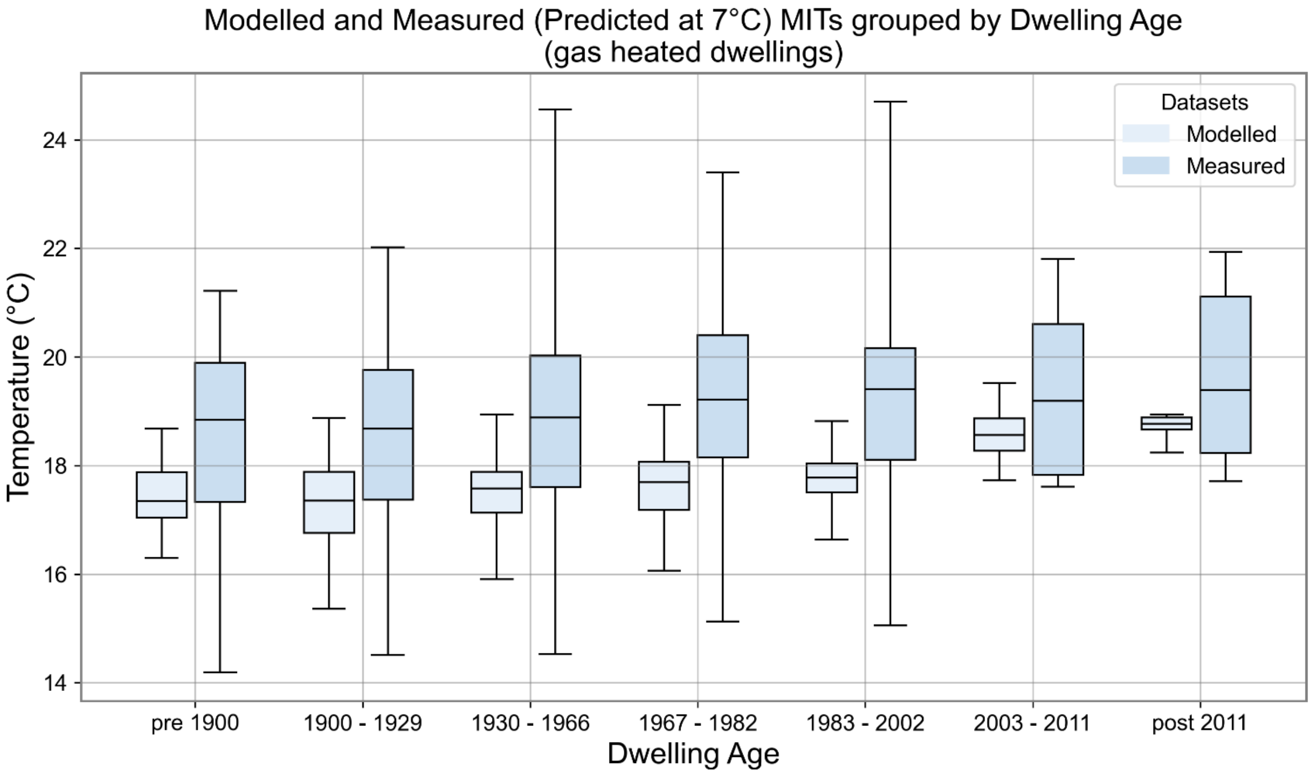


Figure 46 Modelled and Measured predicted temperatures disaggregated by dwelling age as recorded in SERL-NBM metadata.

Noting that 42% of dwellings were built between 1930 and 1966, and only 1% after 2011, this is shown in Figure 46, with pre 1900 properties being approximately 1.1°C cooler than those build post 2011. However, this trend is not reflected in the Measured temperatures, where the difference is less than 1°C.

Table 11 Number of Gas-Heated EFUS dwellings analysed in each age-band category

Age band category	Number of dwellings
pre 1900	33
1900 - 1929	48
1930 - 1966	196

1967 - 1982	88
1983 - 2002	62
2003 - 2011	23
post 2011	12

Heat Loss Parameter

The heat loss parameter provides a description of the rate of heat transfer through the building fabric per degree of difference between indoors and outdoors, per square meter of floor area. It is calculated on a monthly basis for the purposes of SAP and is then used to calculate the utilisation factor as well as the Zone 2 temperature reduction[59]. Control type 1 has the largest temperature reduction for Zone 2; up to 3°C based on a HLP of 6 W/m²Kor above. Control Types 2 and 3 have the same relationship to HLP (temperature reduction = 21-HLP+(HLP²/12)), applied to different assumed heating schedules (type 2 has a separate weekday and weekend heating schedule whereas type 3 has a consistent heating schedule).

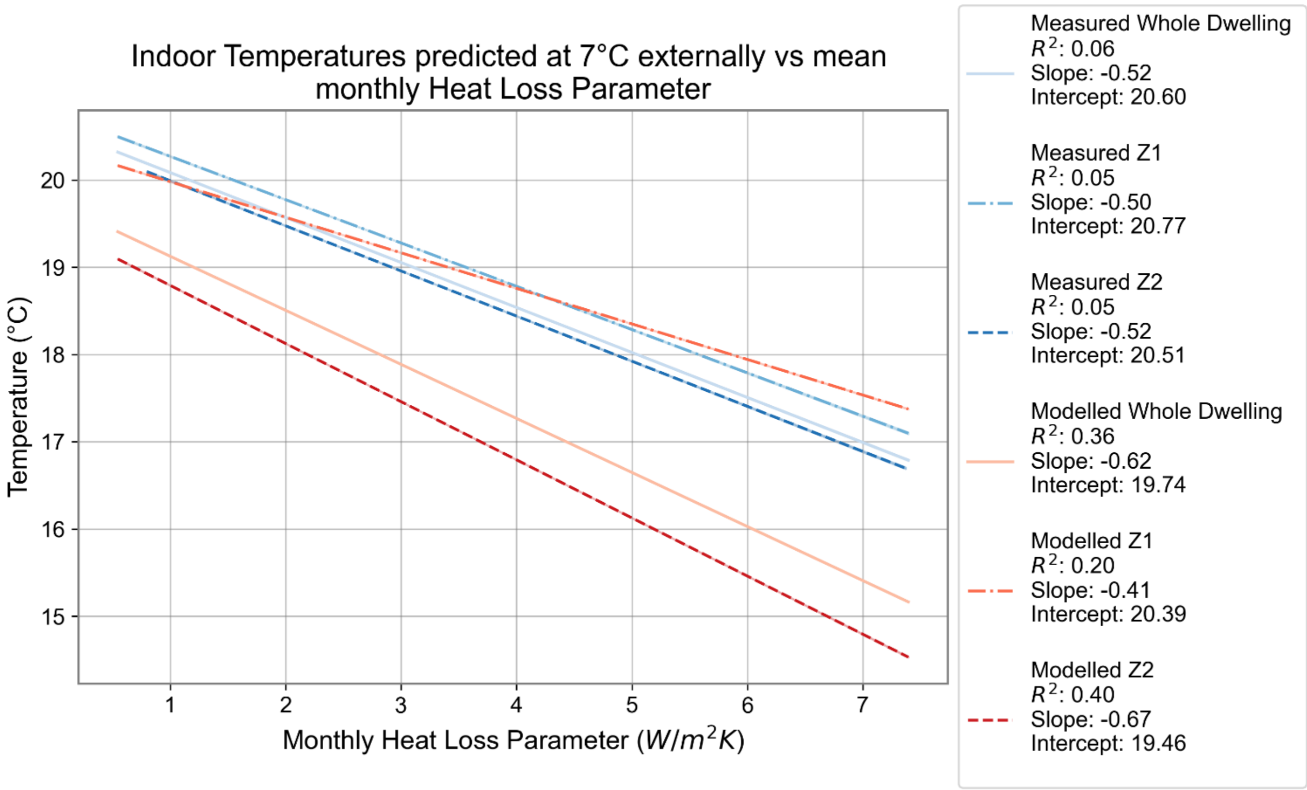


Figure 47 Linear fits between Predicted Measured and Modelled temperatures against Monthly Heat Loss Parameter, disaggregated by Zone

Figure 47 shows the relationship between modelled and measured temperatures and heat loss parameter. In modelled data, the R² values are significantly higher than in the measured data.

[59] See Appendix J for further details.

It is to be expected that modelled data exhibits stronger explanatory relationships between model parameters than are observed in measured data, which has a much more complicated data generating process. However, the degree of difference between modelled and measured R^2 values suggests that the model may be overestimating the strength of the relationship between indoor temperatures and the HLP. Furthermore, it is clear once again that the Zone 2 and MIT temperature assumptions within SAP are overly pessimistic about achieved temperatures.

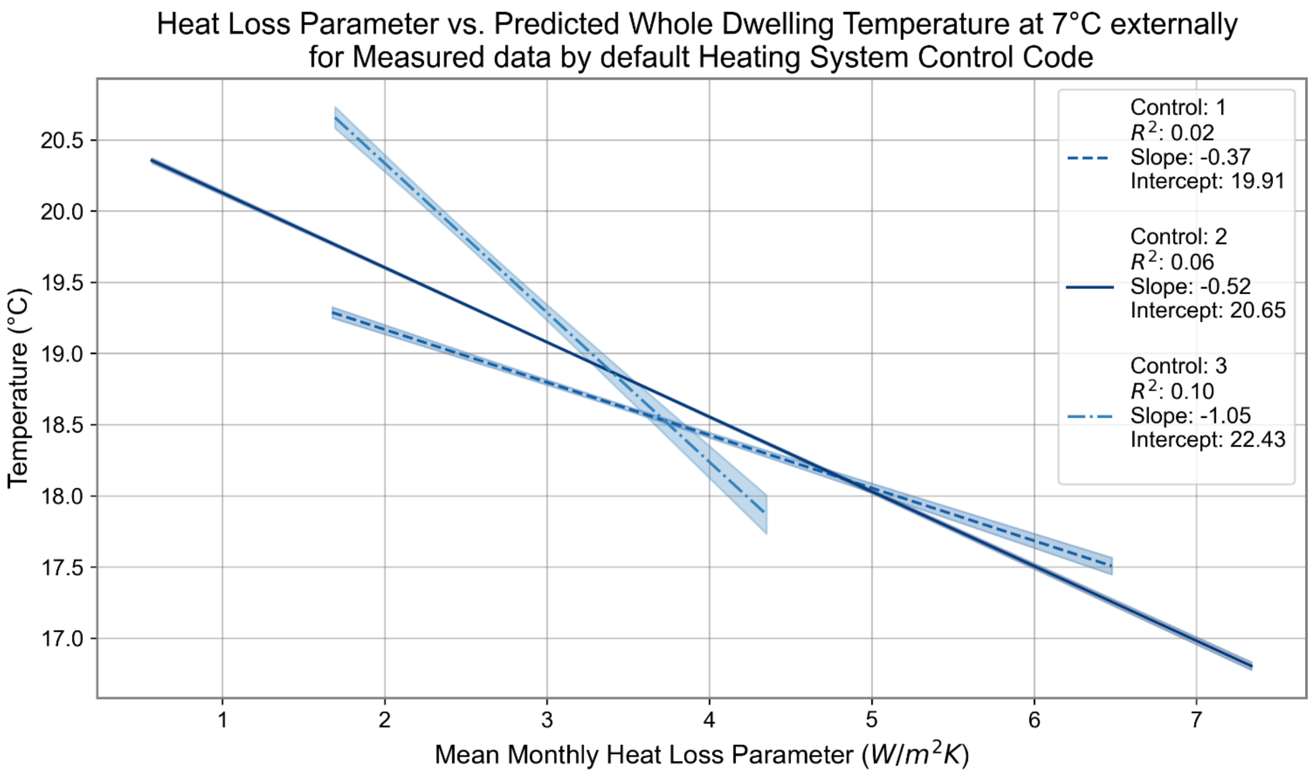


Figure 48 Linear fits for the whole dwelling SIT against monthly Heat Loss Parameter, disaggregated by Heating System Control Type. Control group 1: systems with no timer or thermostatic control or having a programmer but no room thermostat and vice versa, or only a room thermostat. Control category 2: programmers, thermostats, and thermostatic radiator valves (TRVs). Control category 3: both time and temperature control.

Noting that true end points for each regression are supressed for SDC purposes, it is evident from Figure 48 that the most sophisticated controls (category 3) are present in dwellings that are more thermally efficient (lower HLP), while control category 2 represents the majority of dwellings. Although there appears to be a stronger relationship between HLP and predicted temperature in control category 3, it is difficult to draw any firm conclusions on the basis of this plot because the R^2 values suggest that almost none of the variance in the data can be explained by the regression model.

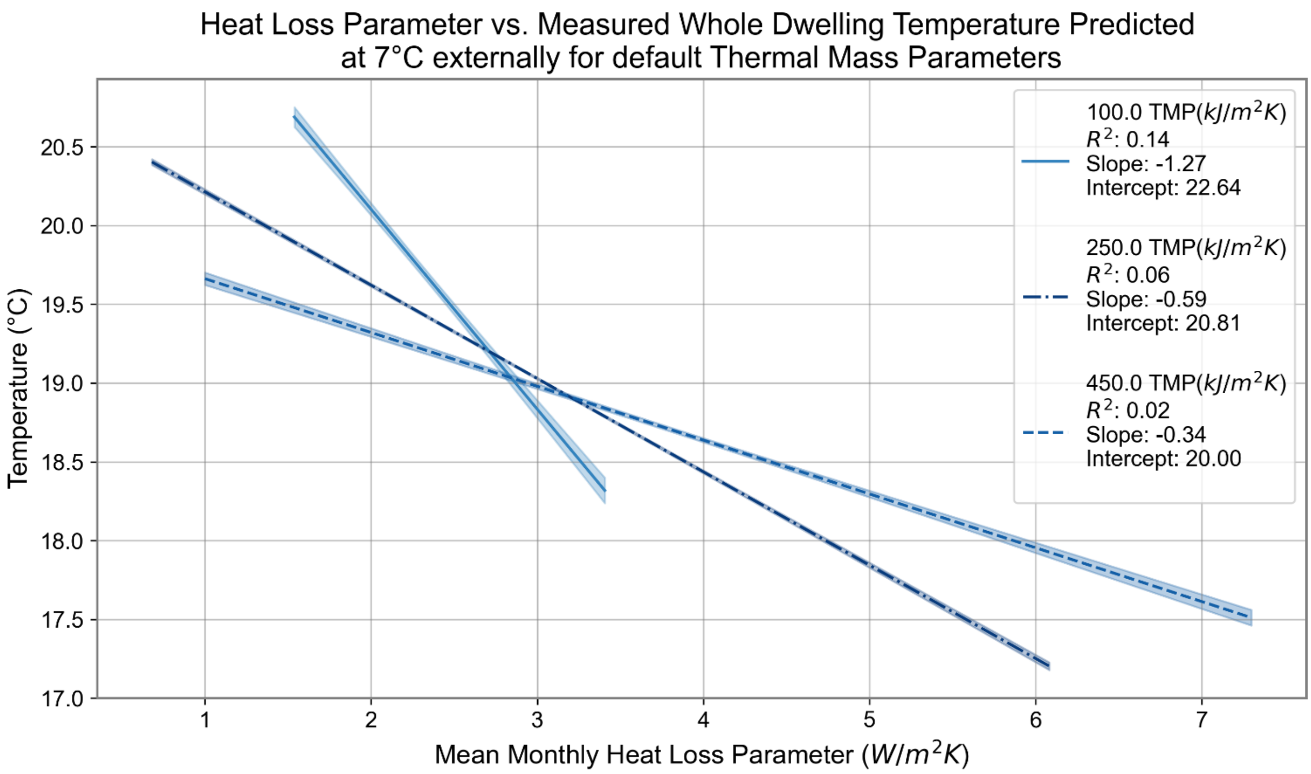


Figure 49 Linear regression of Standardised Indoor Temperature (SIT) against Mean Monthly Heat Loss Parameter (HLP) disaggregated by default Thermal Mass Parameter

The Thermal Mass Parameter is also used in the calculation for the utilisation factor (and therefore space heating requirement), and for the calculation of the temperature reduction when the heating is off. It is therefore plausible that a different relationship between predicted temperature and HLP would be observed for low, medium, or heavyweight buildings (100, 250, 450 kJ/m²K respectively).

Figure 49 shows that although still a very weak relationship that does not capture real dynamics, the R^2 value for the lightweight building is much bigger than for either the medium or heavyweight categories. This suggests that the default thermal mass assumptions may be more accurately capturing building characteristics for lightweight buildings than in the case of medium or heavyweight buildings.

EPC registry analysis: SAP vs RdSAP assessments

The difference in the EPC process between a full SAP and an RdSAP was investigated by analysing the EPC Registry data for homes that have an initial EPC generated when the building is a ‘new home’ (EPC generated via the full SAP process) and a subsequent EPC generated for a ‘marketed sale’ (EPC generated via the RdSAP process). The analysis first considers the difference in whole home EPC band and then the change in individual building elements.

Figure 49 shows the number of homes rated in each EPC band when first rated as a new home and the number of these which move to a different band when they are subsequently re-rated via RdSAP. A large majority of homes are rated as band B when they are new (almost 60,000 homes), however when they are re-rated using RdSAP almost 40,000 of these are downgraded to a C band. It is unlikely that many new homes have introduced changes which significantly decrease their energy performance soon after being built. Homes with a B rating have current energy efficiency ratings of between 81 and 91. The mean and median rating for new homes in band B is 84.0, while the mode is 83. This suggests that the majority of these homes fall comfortably within band B when new. The mean change in current energy efficiency rating is -2.3 (negative value meaning the new home rating is larger than the subsequent rating), and the median is -3.0, however the standard deviation is 6.6 showing that the difference can be large for many homes. A significant number of new homes are band C, and the majority of these are subsequently rated in the same band, although approximately 5,000 of these were upgraded to B on second rating. Upgrades in energy efficiency rating are plausible as improvements may be made to the property, with the addition of solar PV the most likely in new homes.

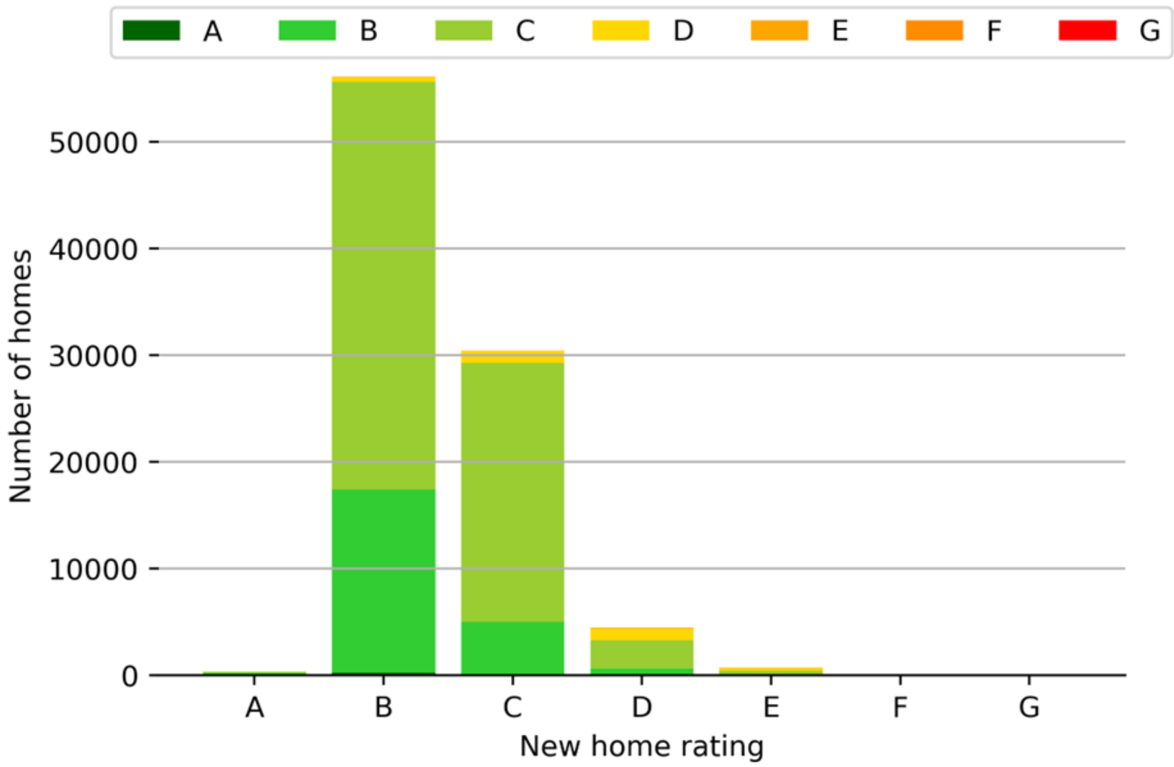


Figure 50 Bar chart of EPC ratings for homes initially assessed as new homes using SAP and subsequently assessed via RdSAP for marketed sales. The full height of the bars

shows the number of homes in each band when new, and the stacked bars show the number of these subsequently rated into each band at the second rating

The absolute values in Figure 49 are dominated by bands B and C but Figure 50 shows the proportion of homes initially rated into each band which are subsequently rated into other bands. This shows that of the small number of homes that are initially rated as A less than 10% of these are again rated as A when assessed under RdSAP, almost half are rated as B, while a significant minority of 35% are downgraded to C. Note that the sample sizes are very small for E, F and G as expected because there are very few new homes with such poor ratings.

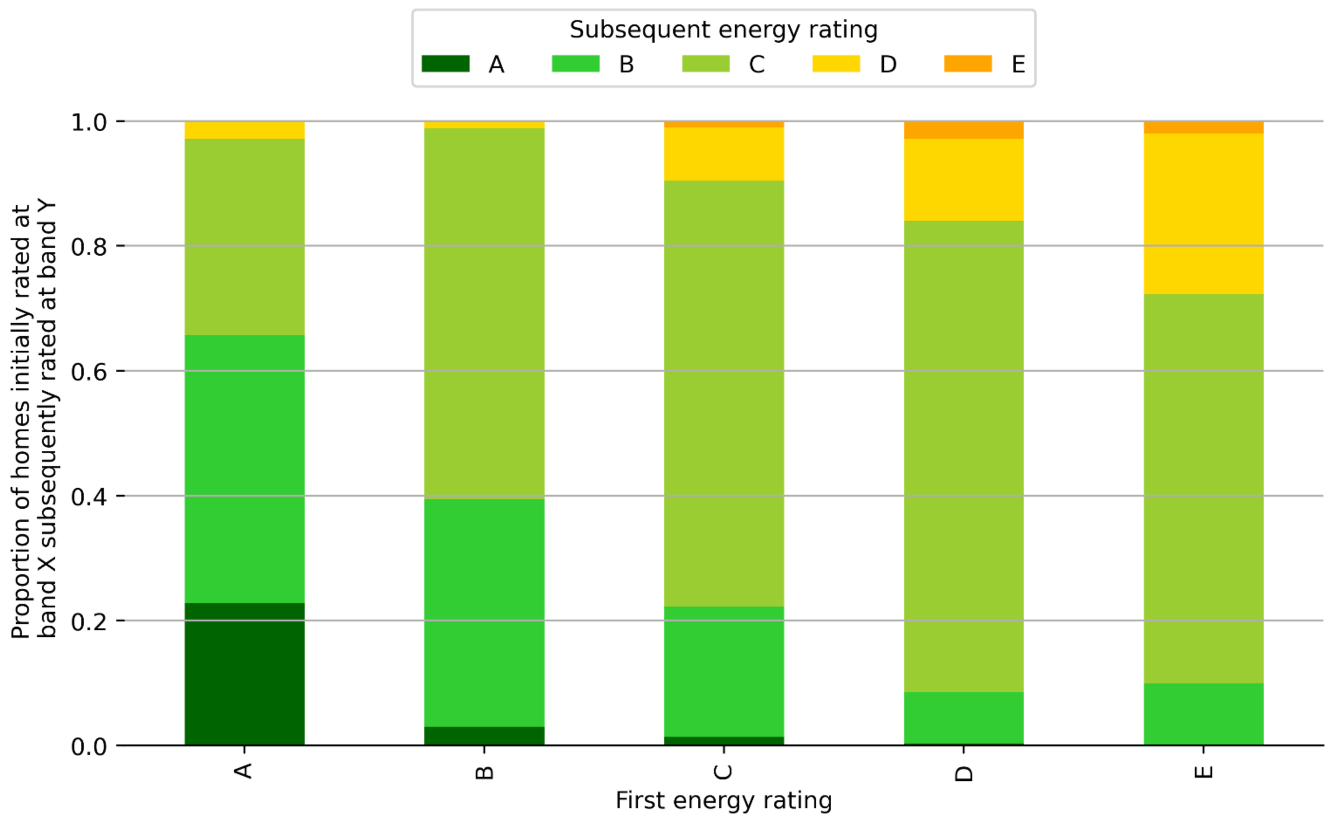


Figure 51 Bar chart of EPC ratings for homes with new ratings and subsequent marketed sale ratings. The x-axis reflects the EPC band when rated as new, and the height of the stacked bars shows the proportion of these subsequently rated into each band when the EPC is generated for a marked sale under RdSAP. Homes with a new rating of F and G have been removed as there were less than 30 homes in these groups (likely change of use from existing buildings).

A possible explanation for the significant number of homes being downgraded from new home to subsequent marketed sale is that there could have been changes to the version of SAP used to generate the ratings. To exclude this effect, we have identified cases where both the new home and subsequent marketed sale assessment were completed using SAP2012. The sample size is much smaller for this group because there are relatively few homes which have been completed and subsequently sold and have had a new EPC since these are only required every 10 years and SAP2012 came into force less than 10 years ago. Nonetheless, the overall picture is largely similar. The new homes are dominated by band B (2,500 homes), with the majority of these (1,500) being downgraded to C when re-rated. The majority of homes initially rated as C maintain this rating after being re-rated. Since the results for this subset of homes are similar to those presented above we have not provided the figures as part of the main text but have included them in Appendix B.

To investigate the parameters are changing from the initial new home rating to the subsequent marketed sale ratings we used the energy efficiency ratings of different building elements on each EPC. We focus on homes which were initially in band B when rated under SAP as new homes and were subsequently downgraded to C when re-rated under RdSAP as this is the largest group of homes moving from one band to another.

Figure 51 shows how the wall ratings changed for homes initially rated as B and subsequently downgraded to C (38,000 homes). The ratings for wall energy efficiency has been stable from at least April 2011 when RdSAP9.90 was introduced to present (note that the thresholds have changed in SAP10.2 but there is no RdSAP equivalent yet in use). The figure shows data filtered between April 2011 and May 2024 (when the EPC registry data was downloaded for this project) to eliminate changes due to a change in the threshold of the ratings. In this period 'very good' walls needed U-values <0.3 W/m²K, and 'good' walls needed U-values between 0.3 W/m²K and 0.6 W/m²K. All 'as built' wall types have the same assumed U-vales in RdSAP for age bands since 2003 as follows: 2003-2006: 0.35 W/m²K; 2007-2011: 0.3 W/m²K; 2012 onwards: 0.28 W/m²K. This means that if a home built between 2003 and 2011 is recorded as having a default 'as-built' wall type then it will always fall within the 'good' category. For almost half the homes the default in RdSAP results in a downgrading in wall U-value (approx. 15,000 downgraded out of 38,000). This suggests that many homes are built with walls exceeding the default U-value but this information is not available when the home is re-rated.

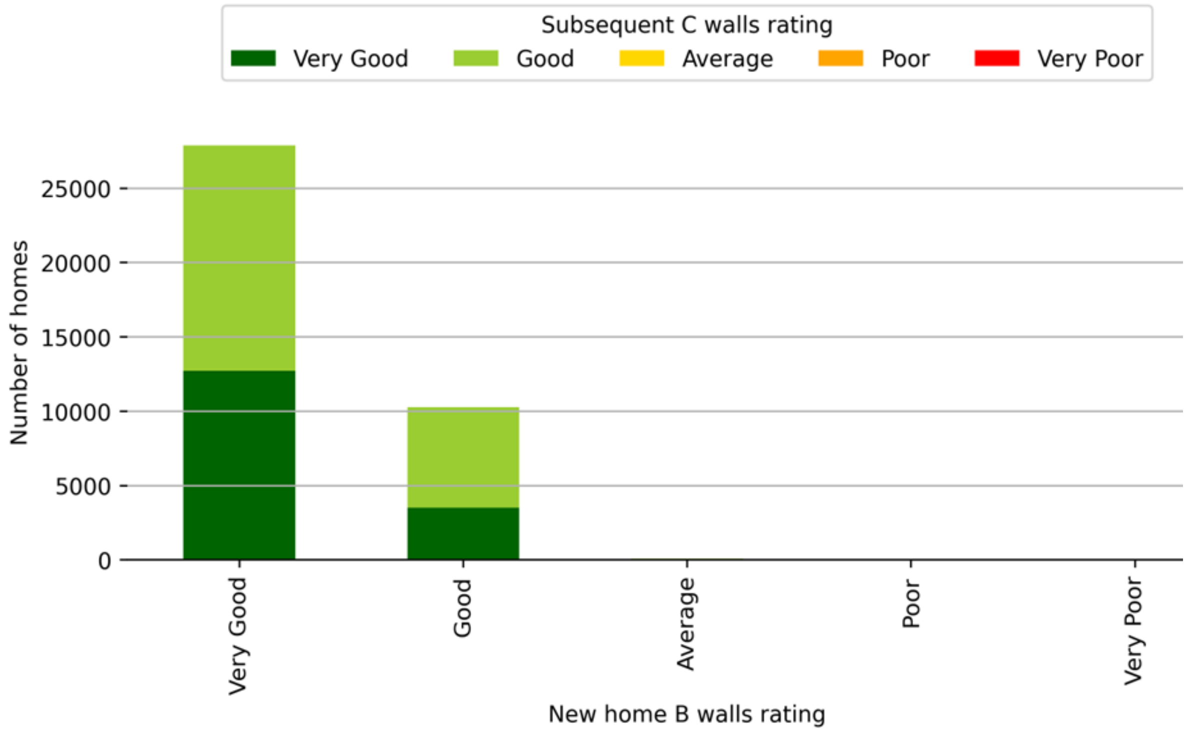


Figure 52 Initial wall rating given to homes with an EPC rating of B when rated under SAP, and the subsequent wall rating when they are downgraded to C under RdSAP.

Efficiency ratings for window U-values have been stable since SAP2009 (introduced in October 2010) to present, Figure 52 shows homes rated in this period which were initially rated as B and subsequently downgraded to C when moving from a SAP to RdSAP rating (47,000 homes). When rated under SAP 36% of homes received a 'good' rating, but this increases to 90% when rated under RdSAP, and only 200 homes initially rated as 'very good' received the same rating when assessed under RdSAP.

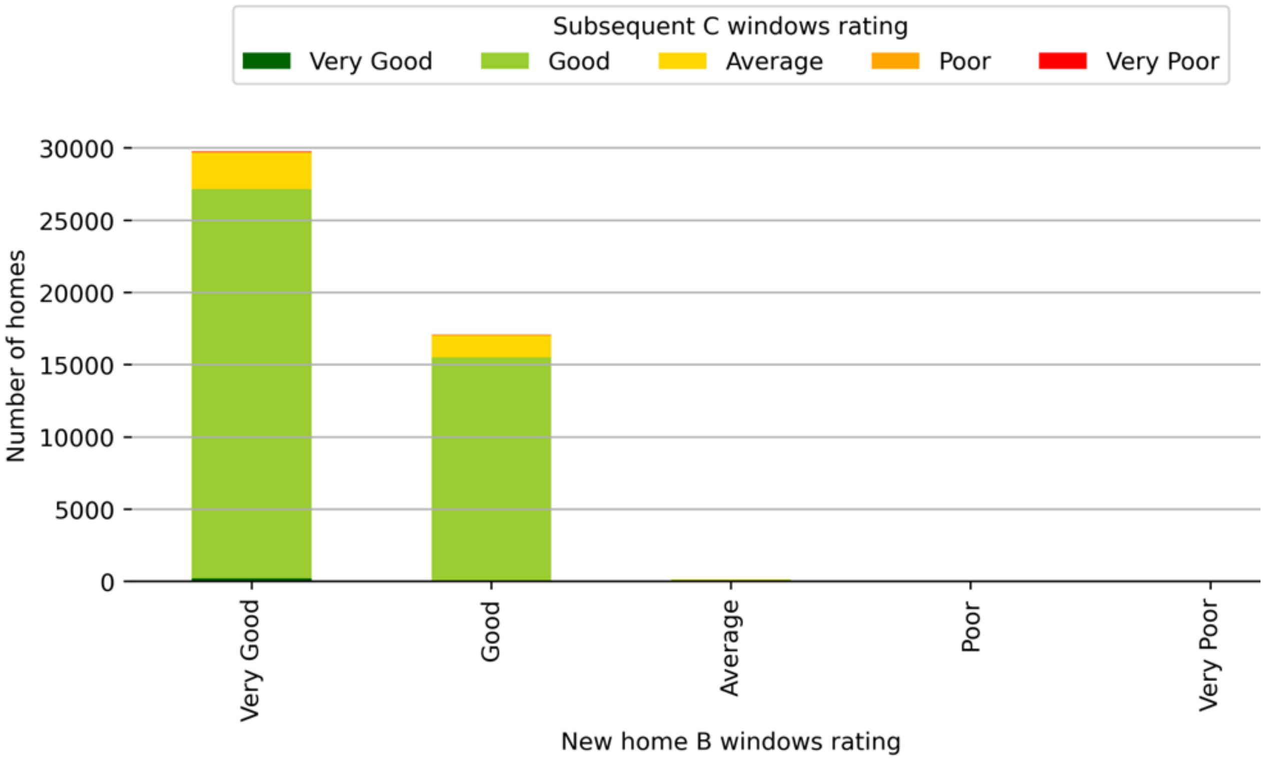


Figure 53 Initial window rating given to homes with an EPC rating of B when rated under SAP, and the subsequent window rating when they are downgraded to C under RdSAP.

To receive a ‘very good’ rating the window U-value must be <1.7 W/m²K while a U-value between 1.7 W/m²K and 2.5 W/m²K is needed for a ‘good’ rating. Double and triple glazing installed since 2002 are assumed to have a U-value of 2.0 W/m²K and 1.8 W/m²K respectively in RdSAP. This means that it is not possible to achieve a ‘very good’ rating without specific evidence or product information. Note that for RdSAP10 double glazing installed since 2022 will be given a U-value of 1.4 W/m²K.

The U-values above can be usefully compared to the requirements in the building regulations. The building regulations for new homes set out notional and limiting U-values for various building elements, the limiting value is a poorest performance allowed for each building element and the notional value comes from a reference building which meets the building regulations as a whole. Between 2010 and 2022 the notional window U-value was 1.4 W/m²K, while the limiting value was 2.0 W/m²K. The building regulations also require that any replacement windows between 2010 and 2022 have a U-value of at least 1.6 W/m²K. The assumed RdSAP window U-values appear to be pessimistic compared to the levels required by the building regulations.

EPC registry: RdSAP to RdSAP rating

Similar analysis was carried out for homes with multiple marketed sale ratings as for the new home to marketed sale analysis above. Figure 54 shows the number of homes rated in each EPC band when first rated and the number of these which move to a different band when they are subsequently re-rated. It would be expected that homes would typically improve in energy efficiency over time, so downgrades are likely to be associated with errors in either the first or second EPC rating[60]. For this analysis we have required that both EPCs were generated using either RdSAP 9.93 onwards since the U-value associated with older solid walls was significantly changed between RdSAP 9.92 and 9.93 and this would likely result in the movement of a home from one band to another. The figure shows that the more homes are rated in the same band for subsequent ratings when both assessments are carried out using RdSAP.

Figure 54 Bar chart of EPC ratings for homes with two marketed sale ratings. The height of the bars shows the number of homes in each rating when first rated, and the stacked bars show the number of these subsequently in each band when the EPC is regenerated via another RdSAP

Figure 54 is dominated by bands D and E in particular, Figure 55 shows the equivalent results presented as a proportion of the homes initially rated into each band. This shows that almost 20% of homes initially rated as B are subsequently downgraded to C (compared to more than 60% for the new home to marketed sale analysis above), and a similar proportion of C homes are downgraded to D. It is also notable that very few homes initially rated into bands E, F or G are subsequently rated into the same band; the vast majority of these homes receive better ratings when they are re-rated.

[60] Crawley, J. et al. (2019) 'Quantifying the Measurement Error on England and Wales EPC Ratings', Energies, 12(3523). doi: 10.3390/en12183523.

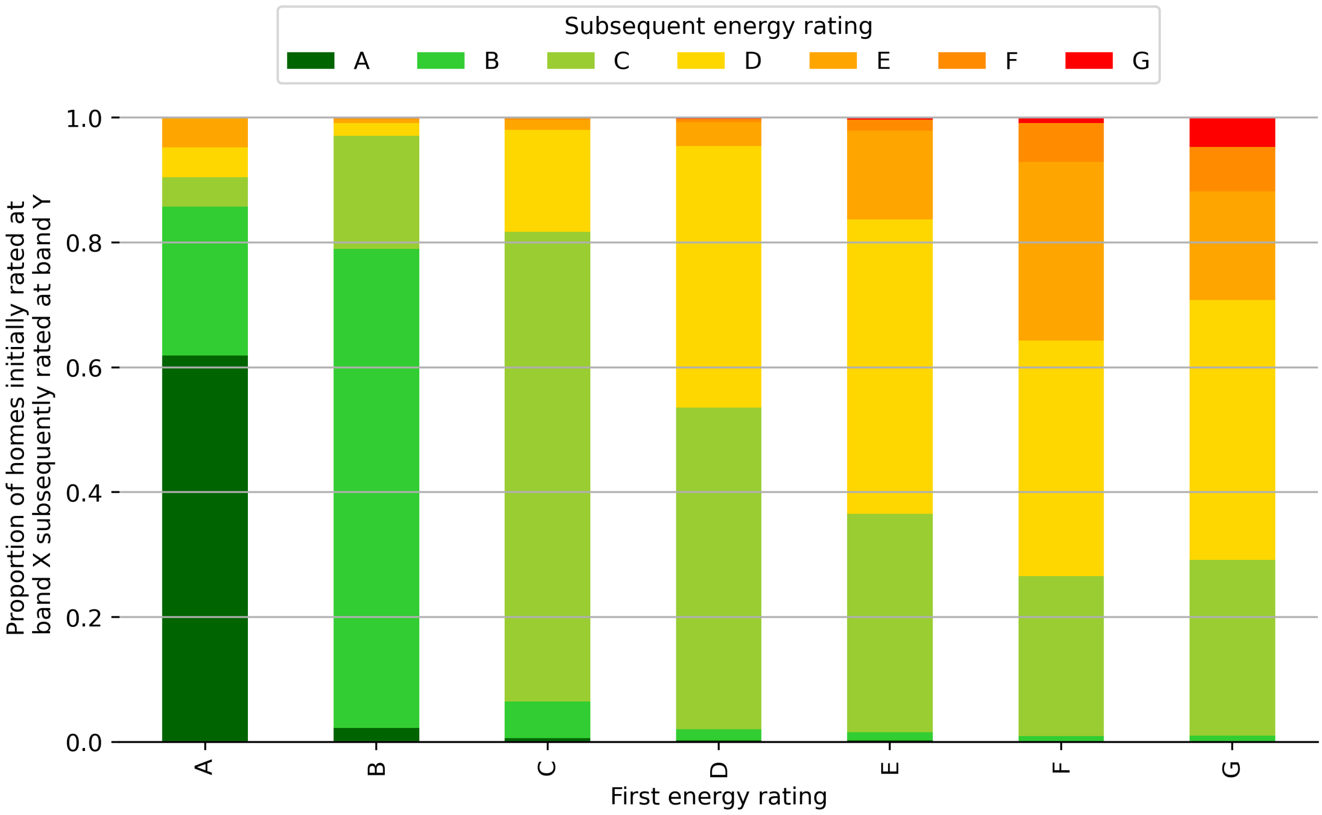


Figure 55 Bar chart of EPC ratings for homes with two marketed sale ratings. The x-axis reflects the EPC band for the first marketed sale rating, and the height of the stacked bars shows the proportion of these subsequently rated into each band when the EPC is re-generated for another marked sale under RdSAP.

Forensic results

Figure 56 compares the EPC RdSAP that is lodged in the EPC registry for the forensic resurveyed homes, compared against a new full SAP calculation. Most resurveys result in an improved SAP rating, this improvement is greatest in less efficient homes, i.e. those homes that were below 60 (band D and below), with 11 homes having an improvement greater than 10 SAP points.

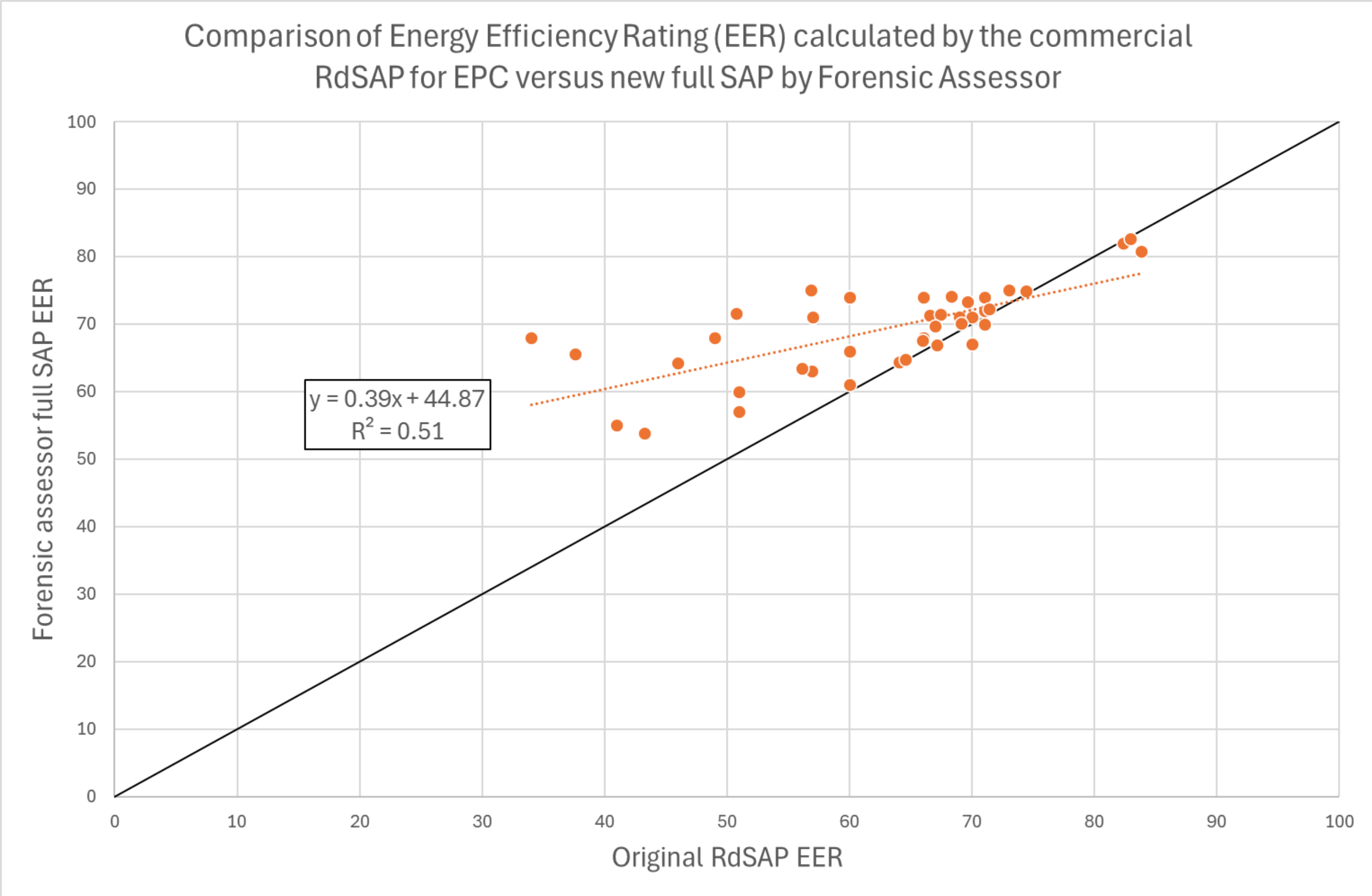
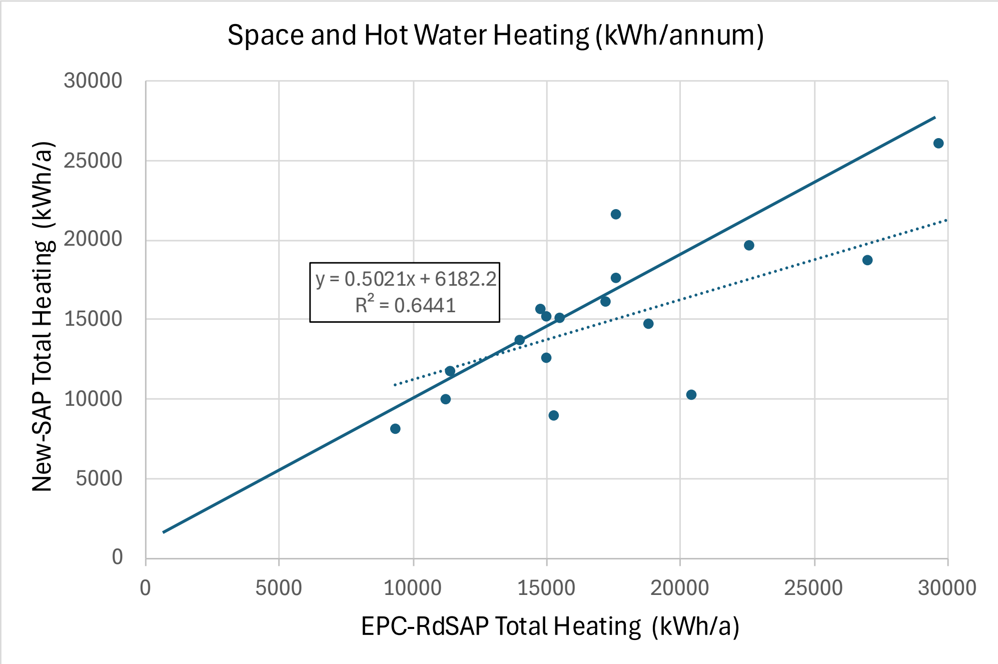


Figure 56 Comparison of EER score between assessment via full SAP from an expert EPC assessor and the existing commercial EPC rating for the same building.

Figure 57 compares the space plus hot water energy use as calculated by the original EPC assessor RdSAP against the new expert SAP (only for 19 homes). It shows that for homes with higher energy use the new SAP has a lower energy use. Figure 57 (right) shows that the reduction in energy use is about 1,000 kWh/a for homes originally rated as C and that this is fairly consistent for homes in this band. However, for D and E rated homes the change increases on average by 377 kWh/a for every SAP point below about 70. Therefore, part of the systematic increase in performance gap in poorly insulated homes is likely due to changes between the original EPC and the new SAP.



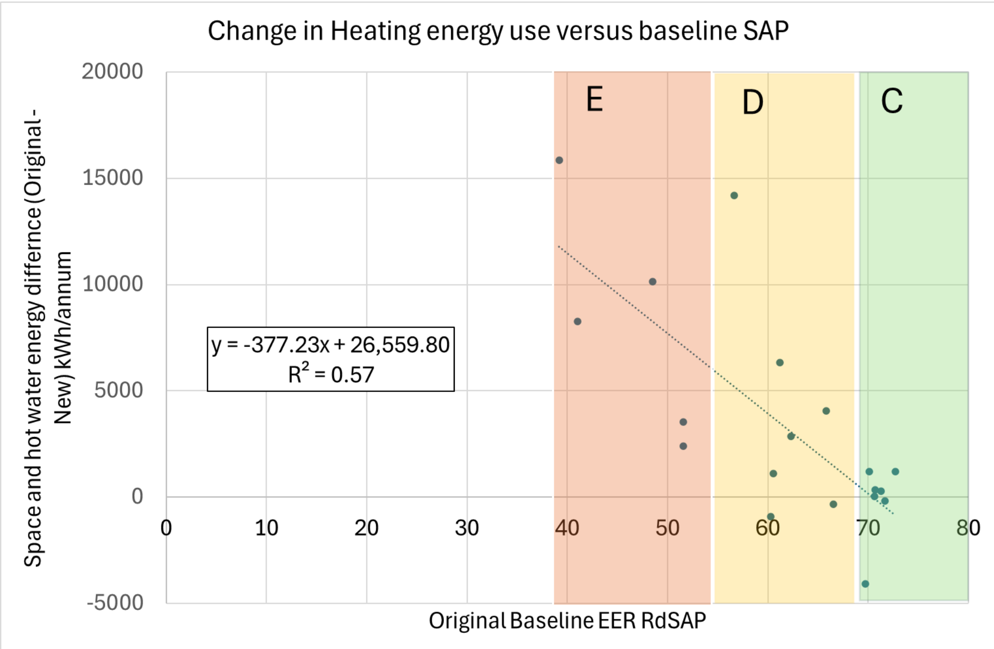


Figure 57 Comparison of change in space and water heating against total heating (top) and against SAP score (bottom) for homes resurveyed by an expert EPC assessor compared to their previous commercial assessment.

Figure 58 compares the original (Commercial RdSAP) performance gap (% difference between modelled and measured total primary energy intensity) with the new gap (Expert SAP) using the forensic full SAP survey results. The average gap shifts much closer to zero by undertaking a full expert SAP at a time when the home was metered.

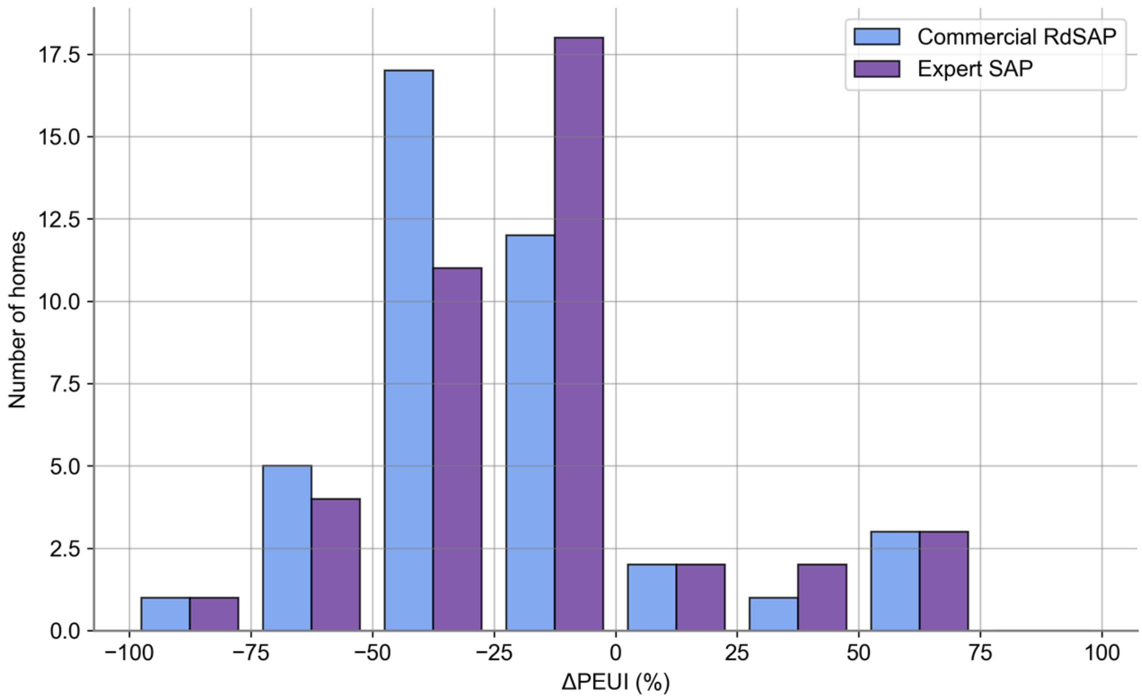


Figure 58 The percentage difference in primary energy use intensity between the metered energy use and modelled energy use for homes assessed by an expert EPC assessor and their previous commercial EPC assessment.

To help identify the main cause of this reduction in the gap, the impact of each change to the calculation was calculated for each of the forensic sites. On average each house had five changes to the calculation. The majority of these individual changes resulted in less than 1 SAP point difference. The mean change in heating energy use was 5%, the median 1%. Only 27% of changes resulted in a space heating change greater than 5%. Changes have been classified as one of the following:

- Measures installed since original EPC
- Assessor error
- RdSAP core process and conventions

Figure 59 shows the average percentage variation caused by these different classified changes to the calculation (for the gas heated homes), showing that the measures installed since the original EPC has the largest effect (10.1%), followed by Assessor error (4.3%), whereas RdSAP process and conventions has a small impact on average (1.6%).

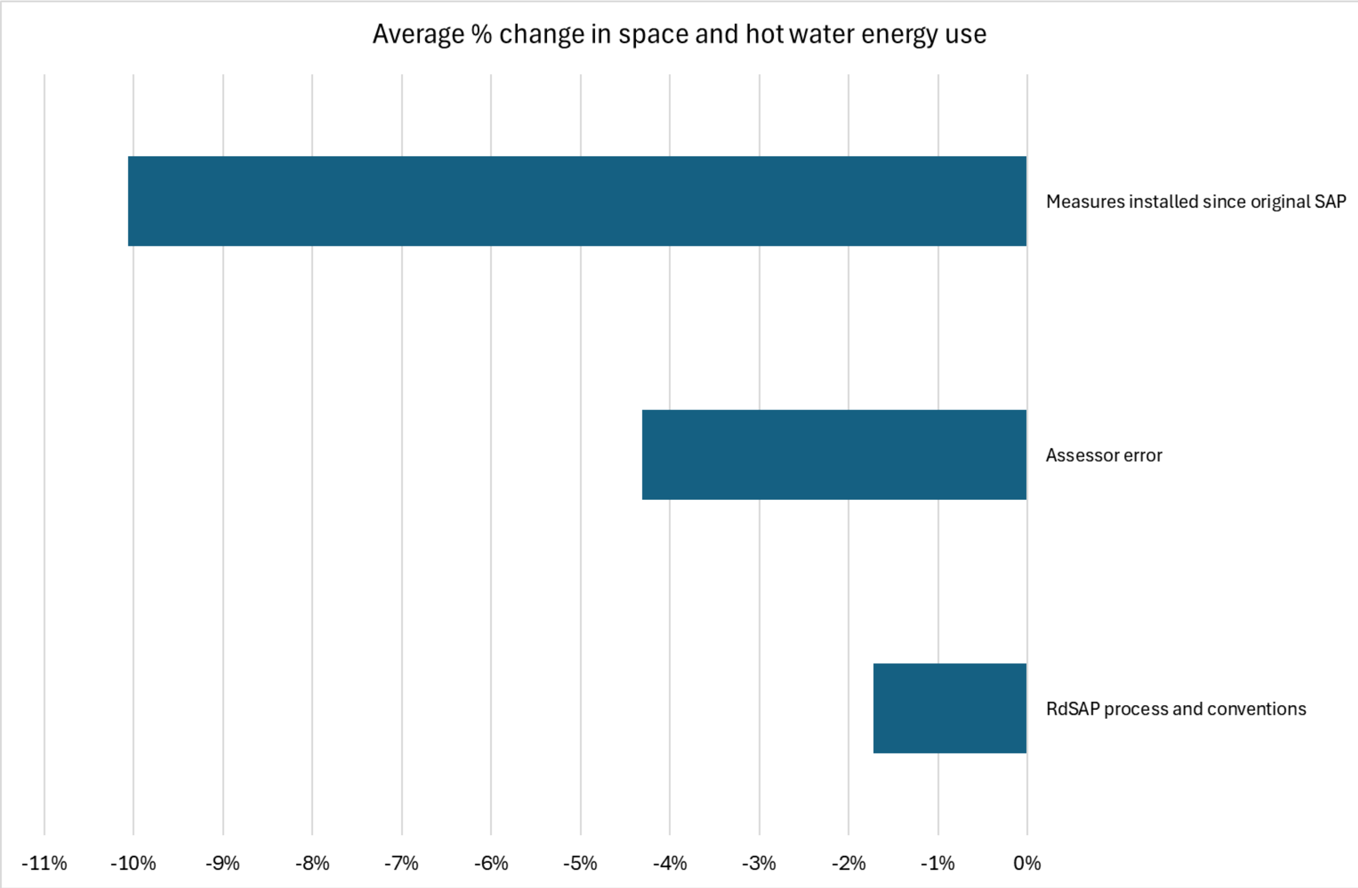


Figure 59 Average change in space and hot water energy use from commercial EPC assessment to expert EPC assessment.

Table 12 lists the changes that resulted in greater than 5% change in total heating energy use (space plus hot water for 19 homes). The full list of changes and their impact can be found in the supplementary document "Space and water heating changes following expert EPC assessment". The biggest changes are due to heating system replacement since the original EPC was issued but pre 2021 when the meter data was collected. This is followed by a range of assessor errors, incorrect classification of heating, loft insulation not recorded, and dimensions incorrectly recorded. Changes to the RdSAP core process and conventions can also have a significant impact, in particular changes to the default assumptions for solid wall U-value, and the treatment of room-in-roof and garages.

Table 12 Changes from commercial to expert EPC assessment that resulted in greater than 5% change in total heating energy use.

Site	Classification of change	Change	SAP EER	SAP change	% SAP change	Space heating (kWh/a)	Hot water (kWh/a)	Total heating (kWh/a)	% Total heating change
A7	Measures installed since EPC issued (pre 2021)	New condensing combi boiler and associated controls to replace gas fire with back boiler and poor controls. Also, more modern double glazing and more low energy lights	66.9	-18.5	38.1%	7639	2125	9764	-52.2%
A8	Measures installed since EPC issued	Boiler has been replaced Upstairs windows have been replaced.	73.6	-12.4	20.2%	6926	2023	8949	-41.4%
A3	Assessor errors	Wrong age band selected (cavity wall insulation recommendation not expected).	70.3	-13.6	24.0%	17945	3569	21514	-36.8%
A3	Measures installed since EPC issued	Cavity wall insulation Low energy lights increased from 32% to 54%	68.2	-11.5	20.3%	20303	3564	23867	-29.9%
A6	Assessor errors	Assessor did not access loft space.	67.6	-5.3	8.5%	15714	2667	18381	-18.6%
B5	Assessor errors	Secondary heating incorrectly classified	48.0	-7.0	17.1%	20439	2498	22937	-15.1%
A9	Assessor errors	Specific boiler not entered from database	75.0	-2.3	3.2%	6092	2090	8182	-12.4%
B7	Measures installed since EPC issued	Boiler and cylinder have been replaced Part of garage converted to utility room, eliminating heat loss floor to garage. 50% LEDs	70.3	-4.5	6.8%	12670	3868	16538	-12.1%
B7	Assessor errors	Incorrect property age (afffects window U-values as well as wall and floor U-values)	68.5	-2.7	4.2%	11804	4852	16656	-11.5%
B2	Assesor errors	Loft insulation not recorded	56.0	-4.4	8.6%	11044	2258	13302	-11.4%
A3	Assessor errors	Garage included in dwelling floor area.	57.0	-0.3	0.5%	26717	3541	30258	-11.2%
A2	Measures installed since EPC issued	Boiler replaced, loft insulation topped up and additional low energy lights	73.8	-3.7	5.3%	7767	2338	10105	-10.2%
B3	Measures installed since EPC issued	Boiler has been replaced (or may be assessor error not recording boiler details), more low energy lights (61% instead of 50%)	73.4	-2.2	3.0%	10477	2225	12702	-9.4%
B5	RdSAP core processes	Room in roof estimates of heat loss areas are too pessimistic in this case	44.9	-3.9	9.5%	22112	2499	24611	-8.9%
B1	RdSAP core processes	Default U-value for solid brick walls changed from 2.1 to 1.7	54.9	-3.4	6.5%	24430	2647	27077	-8.7%
B4	SAP core process	Cannot allow for significant use of instantaneous electric showers	67.2	3.5	-5.0%	12763	1417	14180	-8.6%
B5	RdSAP core process	Default U-value for solid brick walls changed from 2.1 to 1.7	44.1	-3.1	7.5%	22603	2499	25102	-7.1%
A1	Assessor errors	Default efficiency used for boiler	62.4	-2.0	3.4%	10949	2845	13794	-6.8%
A4	Assessor errors	Extension age may have been one band out (cavity wall U-value 1.6 and flat roof U-value 1.5).	62.5	-1.9	3.2%	13733	2391	16124	-6.5%
B4	Measures installed since EPC issued	Secondary gas fire removed, low energy lights increased from 58% to 100%, two entrance doors replaced	72.8	-2.1	3.0%	11136	3454	14590	-5.9%
B3	Assessor errors	Total floor area 12m2 higher than it should be.	70.2	1.0	-1.4%	10558	2684	13242	-5.5%
A4	RdSAP core processes	v9.91 so main wall U-value will have been taken as 2.1 W/m2K.	62.1	-1.6	2.6%	13932	2390	16322	-5.3%
B6	RdSAP core processes	Sloping ceilings at dropped eaves not accounted for.	65.1	1.5	-2.2%	9710	2401	12111	6.1%
B3	RdSAP core processes	Worse U-value of walls to garage, including walls to garage roof space, not accounted for in the EPC calculation	67.0	1.3	-1.8%	12171	2764	14935	6.5%
A1	Assessor errors	Incorrect floor to ceiling height	58.3	2.0	-3.3%	12719	3049	15768	6.6%
B3	Asessor error	Bay roof, ground floor roof and heat loss floors over garage not included in EPC calculation	69.9	1.4	-1.9%	12217	2764	14981	6.9%

Although most of the changes improve the SAP rating some make the SAP rating worse, which in effect means that some errors cancel out in the final new SAP. This is highlighted in the waterfall diagram below, Figure 60, for site B3 which has 4 changes to the assessment that improved the SAP rating, and 4 which make it worse, resulting in a total change of only 1.5 SAP points and less than 2% change in total heating energy use.

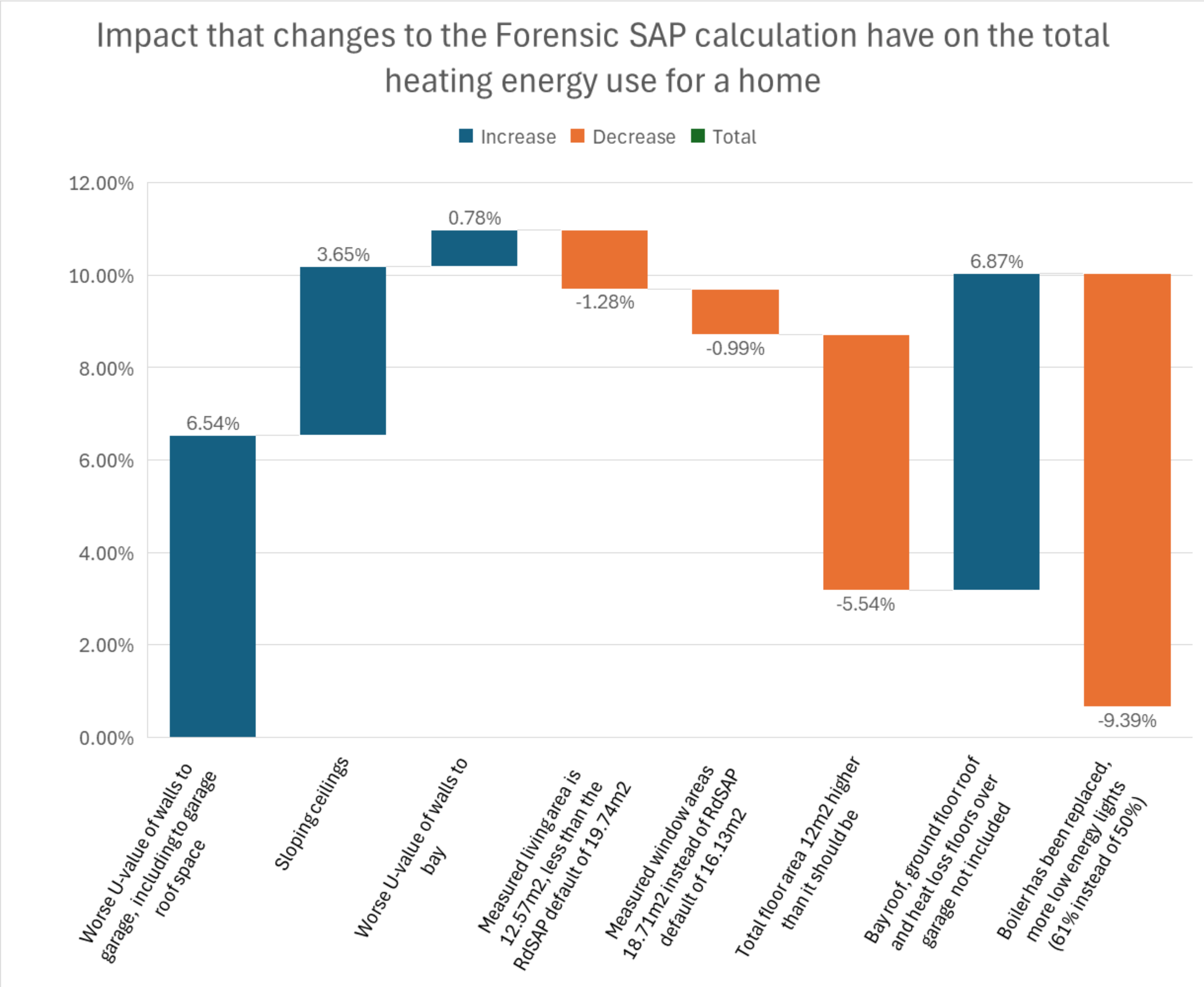


Figure 60 Waterfall diagram showing the effects of various errors and updates from the commercial EPC assessment to expert assessment for one of the case study homes.

The Forensic results show that measures installed since the EPC was issued have a considerable impact on the lodged EPC, corroborating the findings in the modelled scenarios. This suggest that the lifetime of the validity of an EPC should be shorter, or that an EPC should expire when significant changes to a building occur. Only two of the properties had no measures installed since the EPC was issued, although in three cases the only measure was an increase in the proportion of low energy lighting.

The detailed forensic results for each home raise several issues that may appear more widely in the stock. The effect of a boiler change is greater for a band-D or E property. A band-C property is likely to already have an efficient boiler, so a new boiler has relatively little impact.

Two of the properties had significant extensions since the EPC was issued (C2 and C5). This could be a growing trend with increased home working. Some of the RdSAP process issues listed in the forensic reports will not apply once RdSAP-10 is introduced (e.g. assumed window areas). Only four of the surveyed properties had no assessor errors, although it should be noted that assessor errors generally resulted in a smaller impact than the measures installed since the EPC was issued. There was only one flat in the sample of properties surveyed where issues with sheltered walls to corridors arose, this would be expected to arise fairly frequently and may result in greater assessor error for this type of property.

Discussion – Part 1 Gas Heated Homes

This section discusses the results in the context of the research questions specified at the start of this report and draws from literature data as well as different methods of analysis.

RQ1. How does the SAP model (including through the modelling of heat loss, ventilation, internal temperatures and summer energy use) impact the accuracy of EPCs?

Firstly, evidence suggests that heating system and fabric efficiency are underestimated in homes that are modelled as being inefficient. In the literature review it was shown that many previous studies have found worsening agreement between measured and modelled HTC (Heat Transfer Coefficient) as modelled HTC increases. The results of the analysis carried out for this project confirmed this finding.

Our analysis showed clear trends in the difference between modelled and measured HPLP (Heating Power Loss Parameter – this is the HTC divided by heating system efficiency normalised by floor area) for homes with different wall types. The modelled HPLP was much greater than the metered HPLP for the least efficient wall types, solid wall and unfilled cavities, particularly for when those homes were modelled using scenario 0 (EPC as-found). The difference was reduced for scenario 4 (fully adapted model: actual weather, RdSAP 9.94, including energy efficiency upgrades lodged in NEED, and thermostat and occupancy numbers from the survey). Meanwhile, filled cavity walls (either as-built or retrofitted) showed a slightly higher HPLP as modelled than as metered for scenario 0, but a slightly lower modelled HPLP than metered for scenario 4.

Very similar trends were observed for different roof types, heating system efficiencies and for building age bands. Taken together, these results suggest that homes with the least efficient wall types tend to have significantly overestimated heat loss in EPCs as-found, and while they improve notably with updated RdSAP versions and updated information about the installed energy efficiency measures, the heat loss remains overestimated for this group of homes. On the other hand, after updating the model for the most efficient homes the heat loss is underestimated suggesting that some characteristics of these homes may be optimistically modelled. Overall, the changes introduced by incorporating the post-EPC improvements recorded in NEED were very important in reducing the average HPLP and bringing it closer to the measured value. This suggests that automatically incorporating the improvements recorded in NEED into the EPC assessment could significantly improve EPC outcomes with relatively little additional burden since the mechanism for recording this data is already in place.

Secondly, evidence from the EFUS temperature data analysis finds that SAP assumes a lower mean internal temperature in the non-living room area (zone 2) of the house than is observed. This assumed lower temperature in the SAP calculation is partly driven by assumptions about how heating system controls impact Z2 temperature. Moreover, the actual difference between zone 1 and 2 is on average much less than is modelled. This means that the measured MIT is higher than the modelled MIT and if the measured temperature was used in the model, then it would cause the energy performance gap to be even greater. However, as noted above, we also measure the heat loss to be smaller than is modelled. If the measured heat loss were used in the model then the energy use would decrease and the internal temperature would increase. It is unclear whether doing this would cause the modelled energy and temperature to match or not, this is out of scope for this research project but could be an area of further work.

Thirdly, SAP assumes greater electricity use throughout the year than is observed in practice. The modelled electricity use is also more seasonal than the metered energy use, with the greatest discrepancy in December. This discrepancy is particularly significant when the parameter used for comparison between the model and reality is cost or primary energy based, because electricity is more expensive and has a higher primary energy factor than gas. It should be noted that any adaptation to the winter electricity use will have a corresponding effect to the gas use, since all electricity use effectively contributes to heating via incidental gains. This means that amending the electricity use to more closely mirror the modelled demand would not improve the total energy use agreement.

Additionally, SAP assumes a lower summer gas use than is observed in the metered data. This suggests either greater energy use for hot water (due to greater hot water use or poorer efficiency), or greater gas cooking, or even more occasional summer heating than is modelled. In particular, we observe that the discrepancy between metered and modelled baseline gas use widens significantly when the NEED improvements are included in the modelling (scenario 3). This suggests that some of the NEED improvements to hot water efficiency that are modelled in SAP are not observed in metered data.

The energy and HPLP performance gap corelates with secondary heating. This suggests that secondary heating plays a significant role in the performance gap and that SAP does not model what occurs in practice. Although secondary heating is only registered in 12% of EPC rated homes, self-reported secondary heating occurs in 35% of the SERL sample. Secondary heating is most prevalent in homes rated E to G in part because the occurrence of secondary heating makes the SAP rating worse.

This analysis did not measure ventilation rates as this was out of scope, however ventilation heat loss is highly significant to overall energy use, especially as modelled in the least efficient buildings. We showed that the median monthly modelled ventilation rates for homes in the

EHS sample was 0.70 ach. The distribution varied for different EPC bands with the median for A&B homes being 0.64 ach, and the median for F&G being 0.85 ach. SAP enforces a minimum ventilation rate of 0.5 ach to match the minimum ventilation rates required under Part F and considered sufficient for adequate indoor air quality. It is currently not known whether the modelled values are likely to be appropriate as there is no large-scale dataset of empirical ventilation rates for UK buildings (note that there is more empirical data on airtightness but translating this to in-use ventilation rates is challenging). Most recent empirical ventilation measurements have focussed on small numbers of case study homes, but nonetheless generally find average ventilation rates well below the minimum 0.5 ach threshold used in SAP (DESNZ, 2025[61]; Ashdown, 2024[62]; Van Rooyen, 2024[63]; Roberts et al., 2023[64]; and Few, 2021[65]).

EPCs accounts for solar gains and the impact this has offsetting space heating costs in a simplistic way in SAP 2012 making assumptions about glazing area, overshading and orientation. Energy consumption during April 2021 was significantly impacted as the sunniest month on record. SAP shows a smaller sensitivity to the impact of solar gains that month than metered data suggests. This should be an area of further analysis since RdSAP-10 requires window areas to be measured not modelled, see Appendix I.

RQ2. How does the RdSAP process, through its use of defaults and changing conventions over time, affect the accuracy of EPCs? And how does this differ from the full SAP process?

Analysis of the EPC registry suggests that there is a significant difference between a full SAP and an RdSAP in terms of the outcomes for a particular house. Of the homes that are rated A under RdSAP when they are new, less than 10% are rated as A when they are re-rated under RdSAP. Almost half are subsequently rated as B, while 35% are rated as C. This is a large and systematic effect. Further analysis of the registry showed that many of the ratings for different building elements were downgraded on re-rating, i.e. there did not appear to be one parameter driving the downgrading across the homes. The downgrading of building elements appeared to be associated with the default values to be used in RdSAP for buildings of particular age bands. We found that where the rating for a building element was better than the default value when rated under SAP, it was likely to be downgraded when reassessed under RdSAP. A potential solution to this would be to make the full original SAP as built when new accessible to the Energy Assessor when they are carrying out a subsequent RdSAP assessment. This

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[61] DESNZ (2025) Evidence to support an update to the methodology for estimating infiltration rates in SAP: Gathering evidence to improve airtightness in the UK housing stock. Department for Energy Security & Net Zero.
[62] Ashdown, M. (2024) A Stochastic Differential Equation model for natural air exchange in unoccupied buildings. University College London.
[63] Van Rooyen, C. (2024) The relationship between ventilation practices and indoor environmental quality in British homes. University College London.
[64] Roberts BM, Allinson D, Lomas KJ (2023), "Evaluating methods for estimating whole house air infiltration rates in summer: implications for overheating and indoor air quality". *International Journal of Building Pathology and Adaptation*, Vol. 41 No. 1 pp. 45–72
[65] Few, J. (2021) Ventilation in occupied homes: measurement, performance and sociotechnical perspectives. University College London.

would mean that the detailed information gathered and used for a SAP is not lost when the next assessment is carried out.

It was only possible to carry out the SAP to RdSAP analysis for new homes in the EPC registry as existing homes are not rated using a full SAP assessment under typical scenarios. However, the group of homes that were recruited for forensic analysis had a full SAP assessment by an expert EPC assessor and this could be compared to their existing commercial RdSAP assessment. The changing defaults and conventions in different versions of RdSAP had a relatively modest impact on the overall outcomes of the model on average. For the forensic group of homes this accounted for a 2% change in space and hot water energy use. Similarly, for the comparison between metered and modelled data updating the EPC model to use RdSAP 9.94 defaults (scenario 1) instead of the version originally used to generate the EPC had a small impact on the discrepancy between metered and modelled energy use, and on all the PTG parameters.

RQ3. How does the motivation of assessors impact the accuracy of EPCs?

We found some differences associated with the transaction type recorded for EPCs. The differences for new homes rated under a full SAP compared to a marketed sale RdSAP were detailed as part of the answer to the previous question. It is also possible that assessors carrying out new build assessments are influenced by pressure to reach particular efficiency targets, although social research methods would likely be required to identify this with certainty. We also found that EPCs carried out for ECO or green deal assessments had a higher average HPLP than for other transaction types. This is likely because these homes will be less efficient and therefore targeted for efficiency measures under these schemes. It is also possible that some of these homes were rated pessimistically to ensure they received measures under the schemes, as suggested by Gledhill (2022)[66], although it is not possible to determine whether this took place via analysis of the registry and further social research methods would be required to determine this.

RQ4. What additional factors significantly impact the accuracy of EPCs?

Analysis of the difference between the assessment carried out by the expert EPC assessor and the commercial EPC assessment showed that on average assessor errors were associated with a 6% change in space and hot water energy use. In some cases the error was much larger, and this was typically associated with incorrect building dimensions, or incorrect classification of the heating system or wall insulation. EPC assessors should be better trained to identify and measure these parameters to avoid large errors in the outcomes.

SAP is often referred to as a bottom-up physics-based model, but it is not a purely theoretical model. SAP has a physics-based core, but has components of expert systems-based socio-technical modelling. Given that gathering all the required data to run a wholly physics based model is infeasible for EPCs, SAP contains many simplifications and assumptions in the inputs, computation and outputs of the model. Some of these are based on expert-judgement

[66] Gledhill, T. (2022) A study into the variability of UK domestic energy assessments. University of Salford.

rather than empirical evidence, and others are intended to encourage particular types of domestic retrofit, while other choices impact the relative ratings of different types of homes (e.g. the headline metric is normalised by floor area so large homes are not penalised for using greater amounts of energy). Such issues include:

a. Assumed use of secondary heating
b. Assumed heating patterns
c. Assumed impact of controls on efficiency and Zone-2 demand temperature
d. Assumed minimum ventilation rates and ventilation behaviours
e. Assumed building parameters based on building age, some of which may be pessimistic
f. The use of fuel cost as a metric including, standing charges, export tariffs and self-consumption of PV-generated electricity.
g. The EER using a log scale, bands being uneven sizes, and normalising by floor area.
h. The use of national not regional weather data for the main EER.
i. Assumptions regarding occupancy and the relationship between this and hot water use, lights and appliances.

Buildings models and rating systems will always have to address issues like those above, what is important is that the sensitivity of the model outputs to these assumptions are understood, and that the logic that has been applied to reach these assumptions and choices is understood. Such choices and assumptions can be a major cause of the performance gap and so these must be clearly documented for any EPC model.

Conclusions – Part 1 Gas Heated Homes

This research project has for the first time compared the monthly energy use for hundreds of existing gas heated properties against the EPC rated energy, including correcting model predictions for weather, occupancy and regulated interventions post EPC. In addition, forensic investigations have been undertaken into the causes of discrepancies by visiting 40 homes, and have compared the SAP modelled mean internal temperature with measured temperature in a different sample of 462 buildings. The comparison by fuel and season provides unique insights into the accuracy of EPCs.

BREDEM, SAP and EPCs have evolved over four decades into complex tools to support the net zero transition, energy affordability and energy security. EPCs were never designed to predict the energy use for a home, but to enable the efficiency of one house to be compared against another, independent of occupancy. Do EPCs do this accurately? It was found that the

EPC as-found gives an average performance gap of -16.0% (negative values mean that the metered energy use is less than the modelled energy use), however for band C homes the gap is -6.6% while for band E homes the gap is -34.3%. Moreover, after fully adjusting the model (update to RdSAP9.94, use actual weather data, include energy efficiency measures installed since the EPC and reflect actual occupancy and thermostat set points), the overall performance gap drops to -10.9%, for band C to -4.4% and for band E to -23.5%. The improvement in the outcomes are largely from accounting for the energy efficiency upgrades. To investigate these differences further the HPLP was utilised as the main metric to study the accuracy in space heating system efficiency and the Base Power to study hot water and appliance efficiency, both of which are derived from energy signatures which examine how energy use changes monthly with external temperature.

It is concluded that EPCs have a significant performance gap because they:

- Overpredict winter gas use, overpredict year-round electricity use and underpredict summer gas use.
- Assume controls lower the temperature in non-living rooms (Zone 2 - rest of house) more than measured. Note, the gap is normally attributed to uninsulated homes being underheated. They are, but SAP already takes this into account. No significant evidence was found that on average people maintained a lower temperature than SAP assumed i.e homes were warmer than SAP assumes.
- Assume inefficient homes are worse from a space heating efficiency perspective than metered, most likely because homes are ventilated less than SAP assumes, and the fabric is more insulating than SAP assumes.
- Assume secondary heating has a bigger impact on the cost of heating a home than is metered.
- Assume that combi-boilers save more energy than metered.
- Assume solar gains save less space heating fuel than in metered/measured homes.

A significant way to improve the accuracy of EPCs would be to have them updated automatically when significant changes to the building were undertaken. The NBM modelling and forensic analysis has demonstrated the importance of this, and how this could be done in practice, by using EPC input data held by MHCLG combined with NEED improvement data held by DESNZ and then used in a version of NBM/SAP. This means both the tools and data are available to implement automatic updating of EPCs at minimal cost. This could also reward homeowners if regulated improvements to homes had been undertaken.

Assessor error is significant in some EPCs, and better training and quality assurance could reduce this alongside undertaking a more detailed full SAP rather than RdSAP. Additionally, EPC assessors could be provided with the best administrative data (e.g. NEED, land registry, building passport) to support an accurate EPC Assessment. In particular, when homes that were assessed using a full SAP calculation when constructed are re-assessed, the original full SAP data should be available to provide the best input data for the surveyor.

Currently the UK has one of the lowest costs for undertaking an EPC in Europe. One strategy worth investigating is that the first EPC on a property should be of a higher quality (as is already the case for new-builds). Subsequent assessments would then focus on changes that have happened since the last survey, rather than resurveying from scratch. Our research has demonstrated that it would be feasible for a surveyor when resurveying a house to have the full previous SAP calculation pre-loaded on a computer as a base case to build on and check for improvements.

In the future further developments in machine learning should be able to derive more accurate in-use metrics from smart meters such as those currently under development as part of the SMETER project. These may be able to assist assessors to select the most appropriate heat transfer coefficient for input into the SAP model rather than a heat transfer coefficient calculated from assumed construction details and U-values. Our analysis has demonstrated that it would be possible to calculate a HPLP for most homes with a smart meter and compare that with a modelled HPLP as a check for significant mistakes in the building heat loss and heating system efficiency.

SAP-2012 accurately predicts the metered annual energy use of an EPC-C rated home on average. This is not surprising given the historic calibration of SAP against national monitored energy use. However, this does not mean that EPCs are accurate across the diversity of the stock, it is possible that under certain circumstances many errors can cancel out and a limited calibration exercise cannot identify this. It is asserted that the methods employed as part of our research have demonstrated a range of inaccuracies in the model that may not have historically been apparent by simply comparing annual energy use. With additional analysis it is expected that this method could be further refined.

It is positive that most homes are warmer than EPCs assume, and that poorly insulated properties use less energy than calculated by EPCs. The GB stock is better performing than indicated by their Registered EPCs.

Future Work

The future work that would be beneficial leading on from this report are suggested below, split into those where processes are already in place such that they could be implemented in the short term (within a year), and those that are strategic priorities to improve EPCs over the long term.

Short term

- Validate SAP-10 and HEM. Re-run the analysis presented in this report using the SAP-10 and HEM model predictions rather than SAP 2012. This could involve revisiting the additional homes that the GHG-SMETER project measured when looking at different heating schedules (a small group of participants agreed to adapt their heating schedules as directed by the research team).

- For EFUS homes, compare the SAP ratings generated by a EHS surveyor with the SAP ratings lodged in the EPC registry and collected by an EPC assessor. This would indicate if there is a systematic difference between the two types of survey. This would require addresses or UPRNs from the EFUS data to enable the linkage between the datasets. If access was granted to obtain the EPC input data from the registry, it would be possible to identify the causes of the difference, not just the magnitude.
- Prepare academic papers on the Performance Gap, Mean Internal Temperature and the Energy Signature Method. This would both facilitate wider dissemination of the results and subject the work to additional peer review.
- Undertake a detailed analysis of the impact of solar radiation and wind speed on metered energy use and comparison with SAP/HEM.
- Produce a new calibrated version of SAP grounded in EFUS and SERL data, e.g. make the Zone-2 MIT = Zone-1 MIT, eliminate secondary heating from the SAP calculation, halve the air change rate currently assumed in SAP, reduce the assumed U-value of solid walled and uninsulated roof properties.
- Model validation should be an on-going process instead of a one-off exercise. This is because energy models and their assumptions represent a rapidly evolving socio-technical system. Lessons learnt from this project suggest an annual comparison between EPC modelled and measured monthly data is now feasible using smart meter and other administrative data.

Longer term

- New Build: SERL does not contain any buildings built to the current Regulations and so cannot be used to test the validity of assumptions in any Future Homes Standard (FHS) wrapper. Recruiting 1,000 new homes each year into SERL would enable new build assumptions to be better validated and also rapidly monitor the impact of new building regulations.
- This report has identified a significant difference between NEED annualised (but not weather corrected) energy data and SERL energy data with over half the properties having a difference in electricity use for the same property greater than 10% (presented in Appendix H). Note, all these homes have smart meters so the annualization process should be less important than for homes with traditional meters since meter readings are more frequently available. This difference changes from year to year. Since both NEED and SERL data are key data sets it is important to understand what may cause this difference.
- Monitor the in-use ventilation rate of a sample of buildings assessed by SAP and HEM, which are representative of the GB built stock.
- Create an AI-SAP model trained on SERL and EPC input data. This could be used to generate half hourly, monthly and annual gas and electricity profiles, given SAP inputs and a weather file to form a continuous improvement validation comparison for EPC methodology.

- Compare the SAP predicted PV export predictions with metered data from the SERL sample.
- Investigate the impact of using 3D-stock built form data as inputs to the EPC process. 3D-stock generates a model of every building in a stock using sources including LiDAR and Ordinance Survey data; this may provide more accurate form data for some fields than is collected by EPC assessors.
- During the research, input was collected from several experts in SAP and EPCs who have suggested additional potential causes of the performance gap. For example[67], the impact of a different radiant temperature to air temperature in uninsulated properties, the impact of urban heat island and solar warming of walls. Some of these effects could be tested with the methods presented in this report, others may be better tested via other methods such as detailed building simulation.

[67] David Cronin, personal communication, "Potential causes of over-prediction of energy use by EPCs, 9th October 2023

Part 2: Electrically Heated homes

Introduction

This report builds on the work undertaken in Phase 1 on gas heated homes. It presents the results of analysing traditional electrically heated homes rather than gas heated homes. Homes with heat pumps have been excluded from this analysis.

The next decade is forecast to see a move to electric heating via modern electric heating systems (heat pumps, modern storage heaters, including centralised electric storage boilers, plus panel radiators). Both modern and old electric resistance heating systems operate at close to 100% efficiency converting electricity to heat. However, controls and storage, as well as the balance between radiant and convective heat transfer, can in theory significantly impact running costs and comfort of modern electric heating systems. To help assess the potential benefits of new technologies and new ways of modelling it's important to understand how legacy systems perform and are modelled as a baseline against which new systems may be evaluated.

This report investigates the actual and modelled performance of current electric heating systems by analysing the SERL and NEED databases of energy use in electrically heated homes and comparing EPC modelled data for the same properties. This part of the report also investigates how monitored internal temperatures differ from modelled and how temperatures differ between gas and electrically heated properties using the EFUS dataset.

Also, four electrically heated SERL homes have been visited and expert SAP assessments of the homes undertaken to understand how electrically heated homes are used and modelled.

Background

The DESNZ EPC Accuracy project (Ref BE24022) aims to help understand why the EPC modelled energy use differs from the metered to support the ongoing developments of EPCs and the development of the Home Energy Model (HEM).

The analysis focuses on comparing monitored with modelled energy and internal temperature data for two main samples of homes: SERL and EFUS.

The initial part of the project focused on gas heated properties because these make up most heated homes (74% across England and Wales[68]) and it is possible to disaggregate between

[68] ONS (2023), Statistical Bulletin, Housing, England and Wales: Census 2021

gas use (for heating and cooking) and electricity use (for lights and appliances). However, in the future, homes may be decarbonised by moving towards electric heating via heat pumps which can deliver 3 to 4 units of heat for every unit of electricity (300%-400% efficiency). DESNZ is currently investigating heat pump performance via field trials and model developments such as HEM. However, some homes will not be suitable for local heat pump installation due to site constraints. Therefore, there is considerable interest in modern electric resistance heaters, including infrared (IR) panel radiators, modern storage technologies and sophisticated local control systems that allow flexibility to minimise running costs with time of use tariffs. To understand how these technologies perform compared to legacy systems, it is important to understand how legacy electrical systems perform and are modelled. All electric resistance heating systems are close to 100% efficient at converting electricity to useful heat in the heating season. This means that systems are distinguished in terms of their capacity to provide heat storage, better controls, or a different balance between radiant and convective heat transfer. These characteristics are challenging to model and it can be difficult to know how they will perform in practice compared to legacy systems.

Electrically heated homes in the SERL sampled used 49% of the energy per m² that gas heated homes did in 2021. This could imply that there could be an even greater performance gap for electrically heated homes than that observed between smart metered and EPC-modelled energy use in gas heated homes reported in Few et. al (2023). However, detailed investigation is needed to explore this as the results could differ for electrically heated homes for a variety of reasons. In particular, electrically heated homes in the SERL sample are on average 80% of the size of gas heated homes, they are also often flats which have relatively smaller heat loss area than more detached building types.

Electrically heated homes make up a significant proportion of the worst EPC Energy Efficiency Rated homes because of the relatively high cost of electricity compared to gas. Figure 61 shows that over half of the homes that are F or G rated have electric heating whereas the majority of A to E rated homes are gas heated.

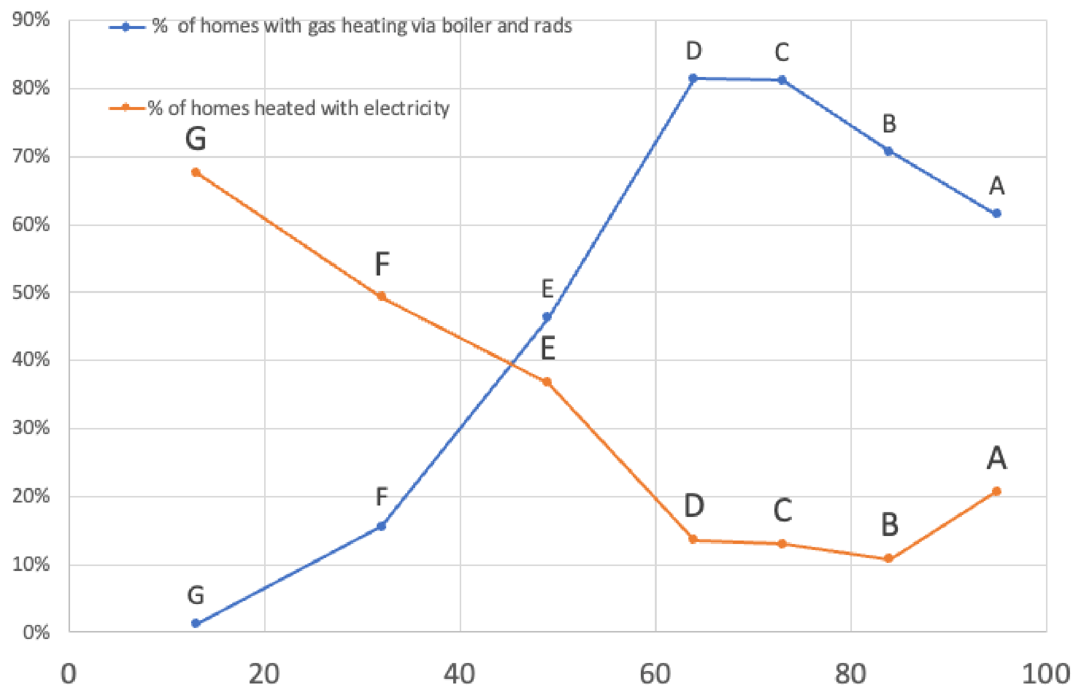

Figure 61 Percentage of homes heated with gas or electric heating for each EPC Band (x-axis EER-SAP).[69]

Figure 62 shows the diurnal variation in electricity use in homes with different types of heating systems, and Table 13 summarises the key values. The peak energy use for storage heaters occurs at 2 am, compared to 6:30 pm for panel radiators and 'other electric'. The peak for storage heaters is almost twice that of panel radiators, and slightly less than twice after normalising by floor area. The 'other electric' group shows higher energy use but lower energy use intensity than panel radiators, suggesting that homes with 'other electric' are typically larger. This could suggest there are some heat pumps in this group although the heating types reported in this figure are self-reported by the occupants and some respondents may find it difficult to classifying their heating system, potentially resulting in some homes with electric radiators being reported as 'other electric'.

[69] This is a simple comparison with data extracted from the DLUHC, England and Wales, EPC database issued on 30th September 2021. This database has been searched for the first 5,000 domestic records in each EPC rating band (A-G) deposited between January 2016 to December 2019 (this is to avoid any COVID related access constraints and to avoid historic versions of SAP software/ methods of depositing data.

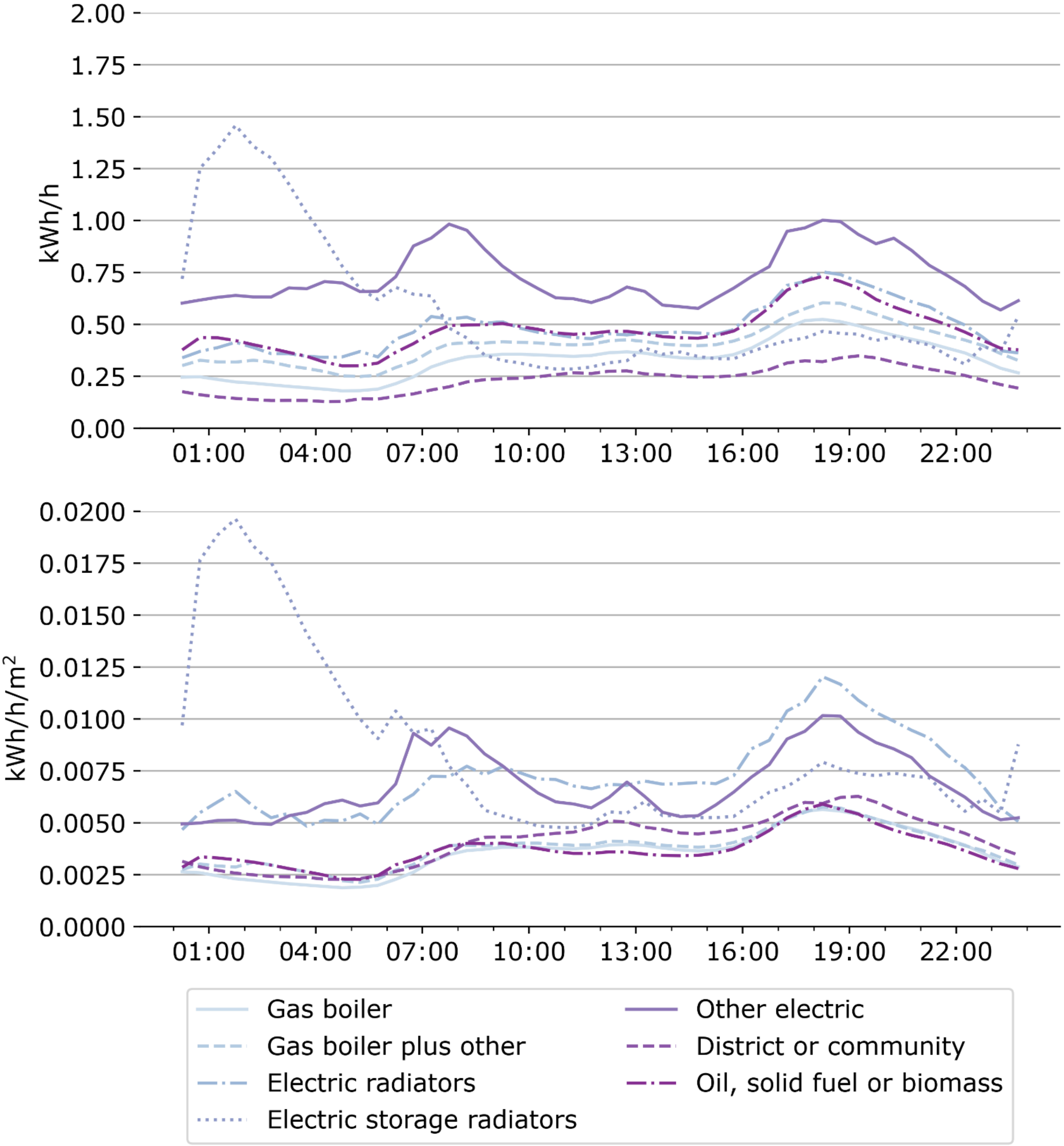

Figure 62 Mean electricity imports, and mean electricity imports normalised by floor area, split by central heating system in 2023. These homes do not have PV. Source [70]

Storage heaters are designed to use energy for heating during off-peak hours, typically between midnight and 7am. On average, the data above shows that 52% of the daily total energy use occurs between midnight and 7am for the storage heater group. It is important to

[70] Few et al, Energy use in GB domestic buildings 2022 and 2023, Smart Energy Research Lab (SERL) Statistical Reports, Volume 2, March 2024, https://serl.ac.uk/key-documents/reports/.

note that this is smart meter data and there is no disaggregation between heating and other energy uses.

Table 13 Summary Statistics for electricity imports shown in Figure 62

Quantity	Minimum	Time of min. value	Maximum	Time of max. value	Central heating type
Electricity	0.18 kWh/h	05:00	0.55 kWh/h	18:30	Gas boiler
Electricity	0.24 kWh/h	05:00	0.64 kWh/h	18:30	Gas boiler plus other
Electricity	0.32 kWh/h	05:00	0.78 kWh/h	18:30	Electric radiators
Electricity	0.27 kWh/h	11:30	1.37 kWh/h	02:00	Electric storage radiators
Electricity	0.53 kWh/h	00:30	1.11 kWh/h	07:30	Other electric
Electricity	0.13 kWh/h	04:30	0.38 kWh/h	19:30	District or community
Electricity	0.28 kWh/h	05:00	0.78 kWh/h	18:30	Oil, solid fuel or biomass
Electricity	0.38 kWh/h	00:00	0.73 kWh/h	18:30	Other or other mix
Electricity	0.25 kWh/h	05:00	0.55 kWh/h	18:30	None

Electrically heated homes make up 8.5% of homes in England and Wales[71] and only 1030 homes in the SERL database of 13,000 homes. Once these homes have been filtered to remove homes with PV and EVs and without EPCs and good quality data then the SERL sample reduces to 60 electric radiators, 50 electric storage and 20 heat pumps. Once the sample has been further filtered to account for the homes which have the required data for modelling in NBM and for which energy signature models can be fitted the sample reduced to 43. The analysis of this sample of homes will have considerable statistical uncertainty given the small sample size. Nonetheless, undertaking monthly analysis and comparing it with NBM predicted monthly energy use will provide useful insights into how accurately current electric resistance heating systems are modelled.

There are 235 electrically heated homes in EFUS, and 36 of these have temperature data. Data from these 36 homes is analysed for insights into the differences between modelled and measured temperature in electrically heated homes. As above, the results are subject to considerable uncertainty given the small sample size.

Analysis of NEED data

Electrically heated homes are relatively rare, consequently, both SERL and EFUS have limited numbers of homes that are solely electrically heated in their samples. This section presents results from the analysis of NEED annualised energy data for 700,000 homes in London, including almost 100,000 electrically heated dwellings[72], the distributions of total energy

[71] ONS (2023), Statistical Bulletin, Housing, England and Wales: Census 2021
[72] Godoy-Shimizu D, Liddiard R, Evans S, et al. Producing domestic energy benchmarks using a large disaggregate stock model. Building Services Engineering Research and Technology. 2024;45(3):217-239.

intensity from this paper, split by dwelling type, are reproduced in Figure 63 and Table 14 below.

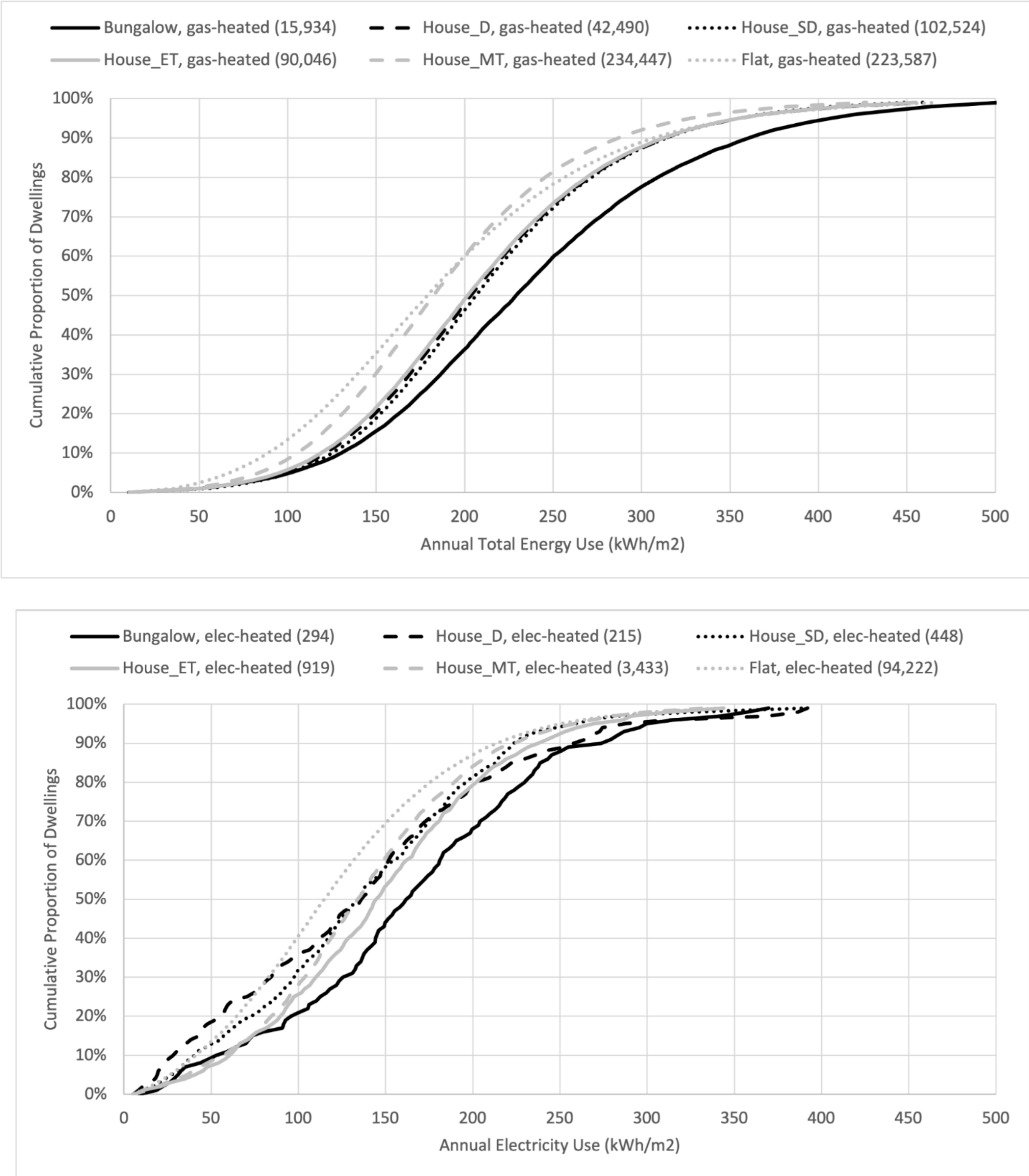

Figure 63 Annual energy use (kWh/m2) profiles for (top panel) total energy use in gas-heated dwellings, and (bottom panel) electricity use in electrically-heated dwellings.

Table 14 Summary results for dwelling performance (kWh/m2)

Dwelling Type	Annual total energy consumption (kWh/m2)			
	Mean	25th	50th	75th
Gas-heated dwellings				
Houses (detached)	212	160	203	255
Houses (semi-detached)	215	163	206	257
Houses (end terrace)	211	157	202	254
Houses (mid terrace)	191	141	182	232
Houses (bungalow)	238	175	229	291
Flats	191	129	179	239
Electrically-heated dwellings				
Houses (detached)	139	71	136	190
Houses (semi-detached)	139	87	134	185
Houses (end terrace)	148	98	144	190
Houses (mid terrace)	139	95	134	176
Houses (bungalow)	165	113	162	216
Flats	124	74	115	162

Within London, total energy intensity was found to be lower in electrically heated homes than gas heated homes across all residential types (bungalows, detached, semi-detached, mid- and end-terrace houses and flats). Across the sample, median total energy intensity was around a third lower in electrically heated homes. This will reflect technological differences (for example direct electric heating is considered to have 100% efficiency, whereas the most efficient gas boilers have ~95% efficiency), alongside differences in the typical constructions and household demographics; electric heating is more commonly found in flats and smaller & newer homes, and a higher proportion of households in fuel poverty are in electrically heated homes[73].

EPCs and electrically heated homes

EPCs are generated for electrically heated homes using the same process as is used for gas heated homes, although there are some special considerations of this group of homes. For dwellings where the information is available (but noted as particularly important for certain technologies such as heat pumps) the Product Characteristics Database should be used to determine electric heating system characteristics (as for gas boilers), because these can vary greatly between models. As noted above, the efficiency for electric resistance heaters (both storage and panel heaters) is considered to be consistent because the conversion of electricity to heat is essentially 100%, the systems differ in terms of their responsiveness, the assumed tariff and the assumed hours of use (partly related to the loss of stored heat). Within SAP, a home's electricity tariff is assigned based on the type of electricity meter and the type of space and water heating present (e.g. if there is a dual meter and electric storage heaters then a 7-hour tariff is assumed). Because the main rating displayed on an EPC, the Energy Efficiency Rating, is a function of the modelled cost of running the building, the choice of tariff is significant for electrically heated homes. For example, in SAP2012 the low rate for a 7-hour

[73] Ofgem. Insights paper on households with electric and other non-gas heating. London: Ofgem, 2015, https://www.ofgem.gov.uk/sites/default/files/docs/insights_paper_on_households_with_electric_and_other_non-gas_heating_1.pdf

tariff is 5.50 p/kWh (high-rate 15.29p/kWh), compared to 7.5 p/kWh for the 10-hour tariff and 13.19 p/kWh for a standard single tariff. All these rates are higher than the gas rate of 3.48 p/kWh, however the difference is only 1.6 times for the 7-hour low tariff, compared to 3.8 times for the standard tariff. SAP makes assumptions on the proportion of space and water heating that is required during the high and low-rate periods, based on the type of electrical tariff and heating plant.

Research Questions

See Part 1 Research Questions.

Data sources

See Part 1 report for detailed description of data sources used in this part of the report.

Methods – Part 2 Electrically Heated Homes

The methods of analysis are as explained in Part 1 of this report. The main difference is that electrically heated homes are not normally on the gas grid so only one fuel is metered, and so heating energy use cannot be disaggregated from other energy uses except by comparing electricity use seasonally. However, there is less uncertainty in heating system efficiency as this report focuses on 100% efficient resistant heating systems, i.e. not heat pumps. This means that the energy temperature gradient is a measure of the heat transfer coefficient of the building, not the heat transfer coefficient divided by the heating system efficiency as is the case for gas heated homes. Additionally, for the gas heated homes a check was performed on the match between NBM modelled and commercial EPC Energy Efficiency Rating (EER) and homes were included in the analysis if these matched within two points. Because of anomalies in the application of high/low tariff rates for electric space heating, this check could not be carried out for the electrically heated homes which has been amended in the NBM between project end and report publication, but the analysis has not been repeated. However, other parameters such as the regulated CO_2 emission rate and energy intensity, as well as the Environmental Impact Rating (EIR) matched well between the NBM modelled outputs and EPC data, suggesting that NBM was performing well at predicting energy use compared to the original EPC model.

Note, sample sizes are very small for electrically heated homes and this limits the results that can be published while complying with statistical disclosure control. The sample is also too small for a robust linear regression as undertaken for gas heated homes, so this analysis has not been performed.

Table 15 summarises some of the key characteristics of the group of 43 SERL homes used for the metered to modelled comparison, and Table 16 gives the mean values of some of the key modelled parameters for these homes by EPC band for scenario 0 (EPC as-found). This shows that storage heaters make up over half of the sample, 81% of electrically heated homes are in flats, hence the low mean floor area (around 50m² to 60m²) and low heat transfer coefficient (84W/K to 185W/K). Very few homes, <5, in this analysis of electrically heated homes had an upgrade lodged in NEED, and these were all fabric improvements. Note that across the whole SERL sample very few electric storage heater replacements have been lodged in NEED, it is not clear whether this reflects a low replacement rate or simply that replacements are not recorded in the datasets that make up NEED.

Table 15 Dwelling characteristics of the 43 homes used for modelled to metered comparison

EPC band	N	Dwelling age	N	Property type		Built form	N	Heating type	N
A & B	2	Pre-1930	3	House or bungalow	8	Detached	3	Panel radiators	17
C	17	1950-1966	3	Flat	35	Semi-detached	19	Storage heaters	22
D	16	1967-1975	8			End-terrace	8	Other	4
E	7	1976-1990	10			Mid-terrace	13		
F & G	1	1991-2002	12						
		2003 onwards	7						

Table 16 Mean modelled values of building parameters for homes in different EPC bands used in the NBM-SERL analysis under scenario 0 (EPC as-found).

	C	D	E
Mean wall U-value (W/m²K)	0.48	0.60	1.22
Mean roof U-value (W/m²K)	0.23	0.48	0.53
Mean floor area (m²)	54.4	57.9	63.0
Mean heating season air change rate (ach)	0.61	0.60	0.63
Mean heating season heat loss parameter (W/m²K)	1.59	2.12	2.91
Mean heating season heat transfer coefficient (W/K)	84	125	185
Mean overall adjusted mean internal temperature (°C)	20.0	19.7	18.5

Forensic investigations

The forensic investigations included collecting detailed building and occupant data in four electrically heated homes. The sample was selected to span a range of building types and ages, Table 17 shows some of the key characteristics of the recruited homes.

Table 17 Key characteristics of the electrically heated homes recruited for forensic analysis

EPC band	N	Dwelling age	N	Number of habitable rooms	N	Property type	N	Built form	N
D	3	1950-1966	1	3	2	Flat	2	Semi-detached	2
E	1	1976-1982	2	4	1	Bungalow	1	End-terrace	1
		2003-2006	1	6	1	House	1	Mid terrace	1

Results – Part 2 Electrically Heated Homes

This section presents the results of the different methods of analysis:

- SAP modelled energy use compared to smart metered data and comparison of energy signature parameters using the SERL sample
- SAP modelled Mean Internal Temperature (MIT) compared to metered MIT using the EFUS sample
- Variation of lodged EPC between original RdSAP and a full SAP at time of metering using the homes recruited for forensic investigation under this project (4 homes)

SAP energy use compared to metered data

Annual analysis

Figure 64 below shows the electricity use for each model as a proportion of the final model (scenario 4) electricity use. The figure shows that the metered energy use is by far the lowest, representing 66.1% of the energy use modelled in scenario 4. The modelled scenarios make very little difference to the overall energy use for these electrically heated homes, with model 0 using only 0.7% more energy than scenario 4. This is a much smaller difference than observed in gas heated homes. The main change in gas heated homes is due to updating the modelling to account for gas boiler replacement lodged in NEED, i.e. changes between Model 2 and 3. There are very few entries of changes in electric heating plant lodged in NEED overall and none within the NBM sample that we were able to model. The changes recorded in NEED for this sample are limited to fabric improvements in a very small number of homes (<5), and furthermore these were moderate improvements rather than changes from very poor to very good performance. Although we did not observe heating system changes it is worth noting that replacement between different electric heating systems can have a big impact on the tariffs and hence fuel cost and SAP rating even though it would have no impact on the modelled space heating energy use.

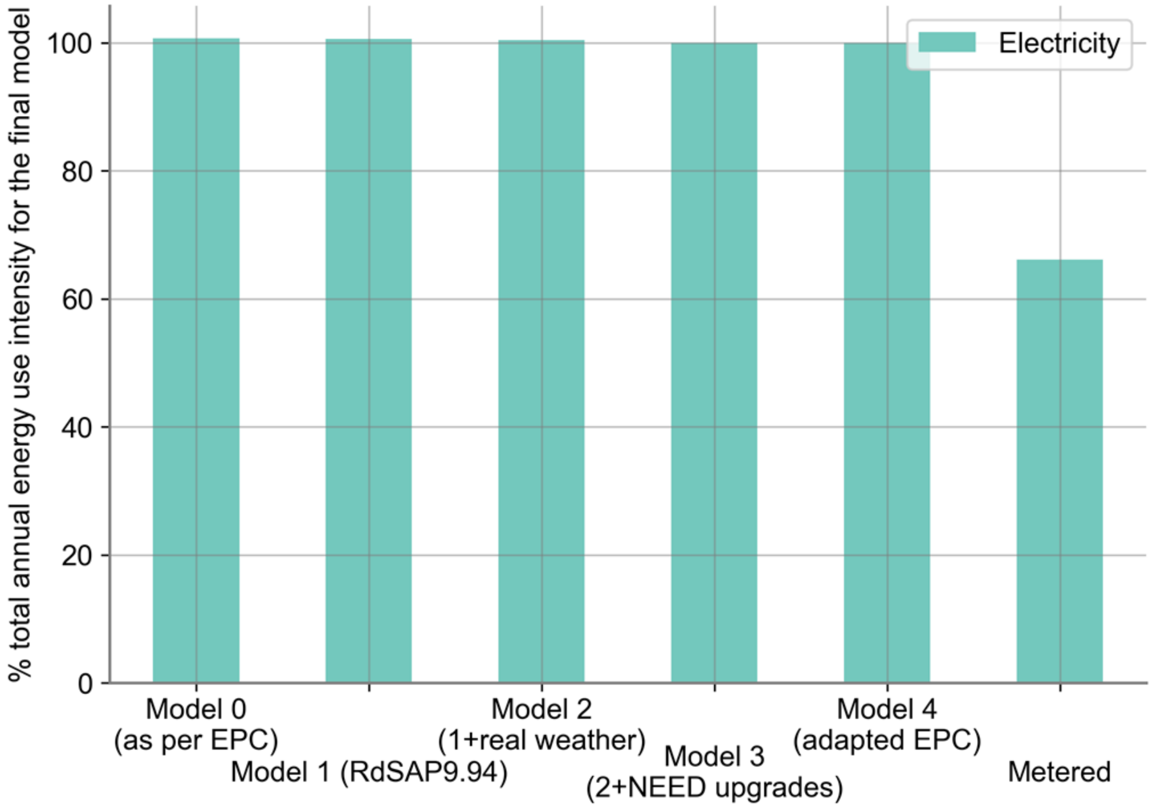

Figure 64 Electricity use as metered and modelled under each scenario as a proportion of the total energy use modelled in scenario 4.

Figure 65 below shows a histogram of the percentage difference in metered-modelled electricity use for model 0 and model 4. The distribution for both models is extremely similar. The distributions are wide, showing that there is considerable variability in the agreement between metered and modelled data on an individual household level.

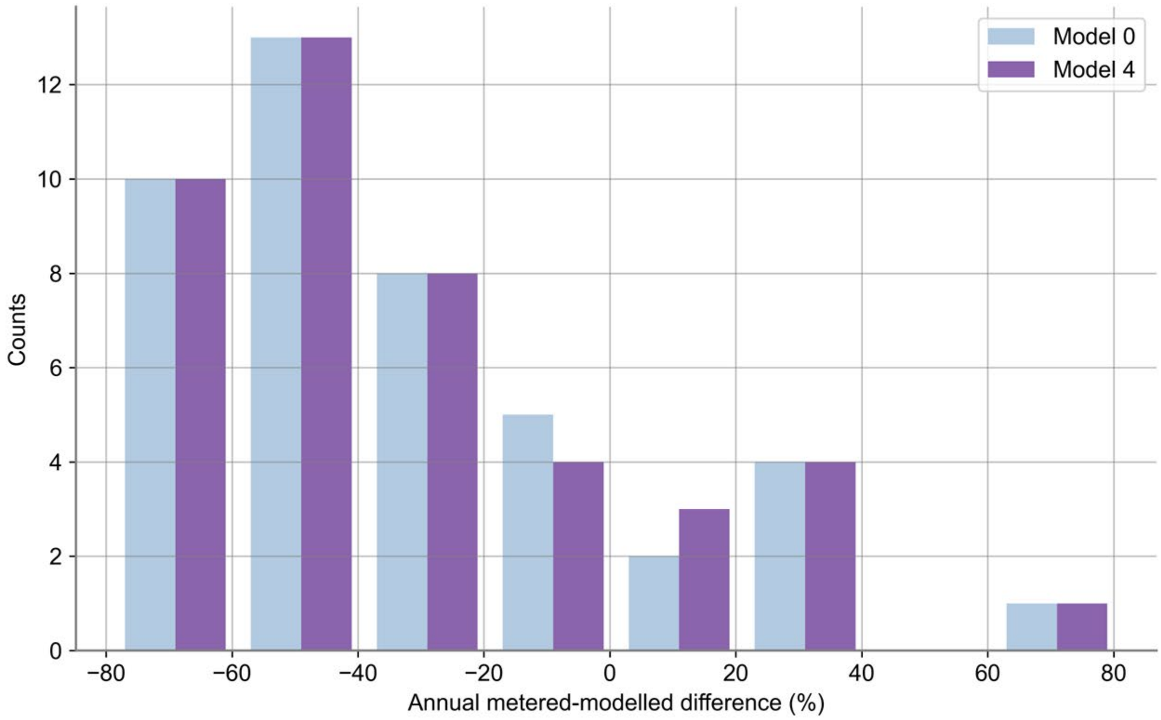

Figure 65 Histogram of the annual percentage difference in metered-modelled energy use for model 0 and model 4.

Figure 66 shows the electricity energy use intensity (EUI) of the metered data and each of the modelled scenarios. For all EPC bands and under all scenarios the average modelled EUI is greater than the metered EUI within the error bars. The metered EUI shows a modest increase when moving from the most efficient to least efficient EPC bands, while the modelled EUI shows a steeper increase across EPC bands. The change in average modelled energy use between all model scenarios is very small.

We find that on average model 0 gives an average performance gap of -31.4%, however the gap is smallest, -20.7%, for band C, and largest for band D homes, -41.2%. This discrepancy is much higher than for gas heated homes for which the mean difference for model 0 for gas heated homes was -16.0%, -6.6% for C-rated homes and -34.3% for E-rated homes.

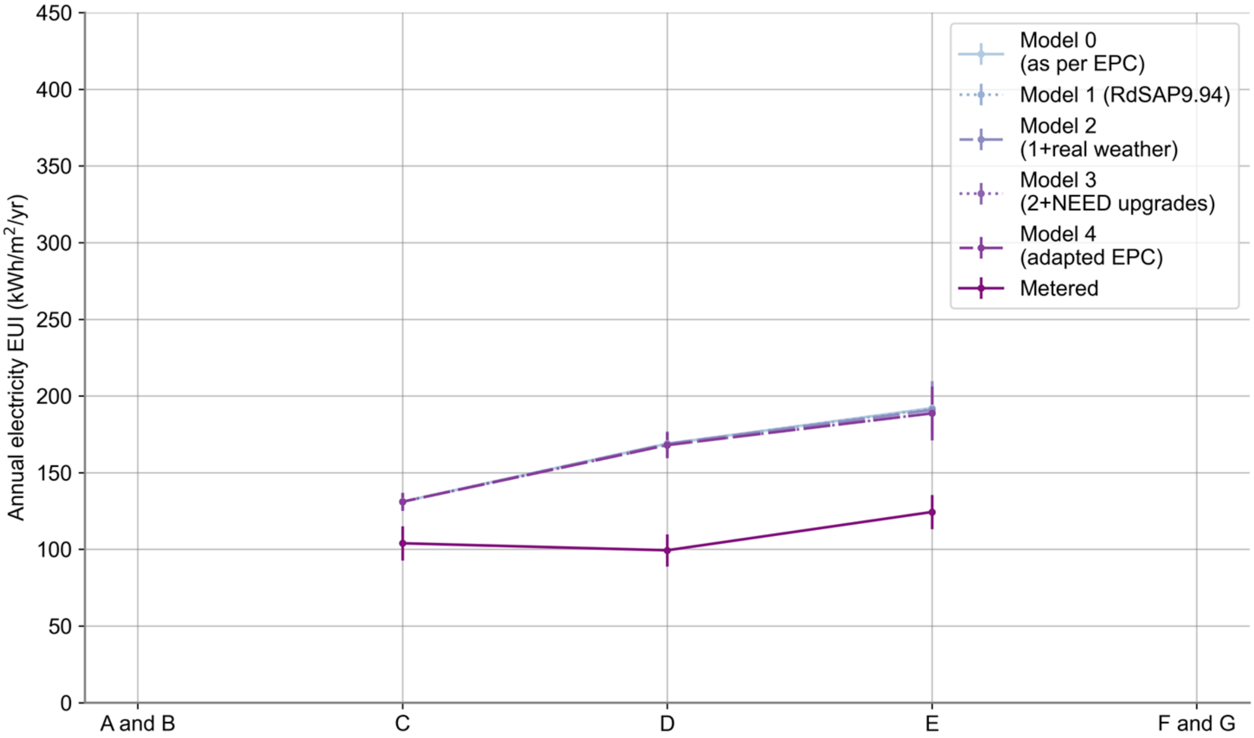

Figure 66 Annual total energy use intensity for EPC bands under each of the modelled scenarios and as metered in 2021. The points and bars represent the mean and standard error on the mean respectively.

Monthly analysis

Figure 67 below shows the average electricity EUI in each month for the smart metered data and for the baseline model (as generated for the EPC) against the month. Throughout the whole year the metered electricity use is less than the modelled for electrically heated homes. The proportional discrepancy increases substantially during the winter, up to a maximum difference of -47% in December to a minimum of -20% in July.

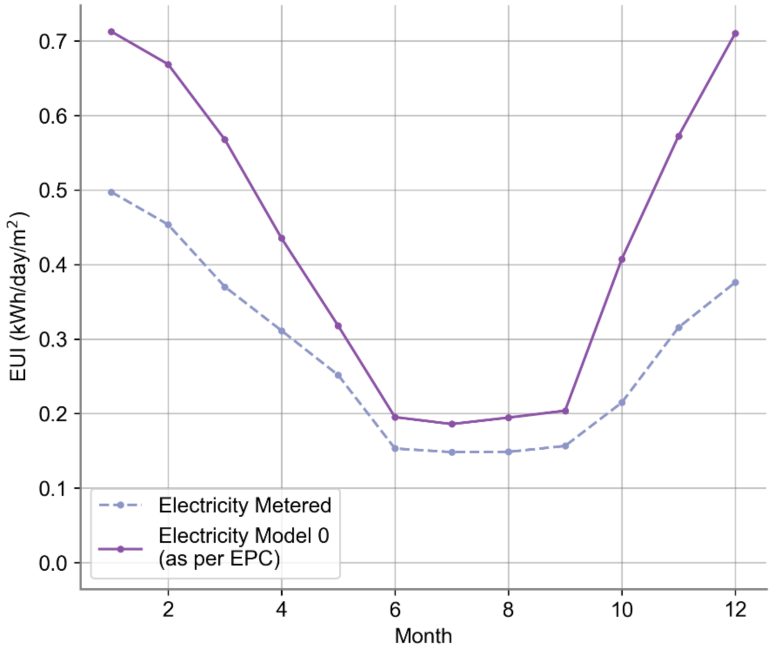

Figure 67 Monthly mean electricity energy use intensity against month as metered and according to model 0 (as per the EPC).

Figure 68 shows the average electricity EUI in each month for the smart metered data and for the baseline model (as generated for the EPC) against the external temperature. This shows that the summer temperatures were slightly warmer for the metered data than the model, and that the coldest month for the metered data was 0.7ºC colder than for the model. This figure also shows a distinct step in the electricity use during the heating season. April 2021 was on average colder than March 2021, but the metered electricity use was lower in April. April 2021 was the sunniest April on record, meaning that the solar gains would have been much higher than usual, and much higher than assumed by the SAP model.

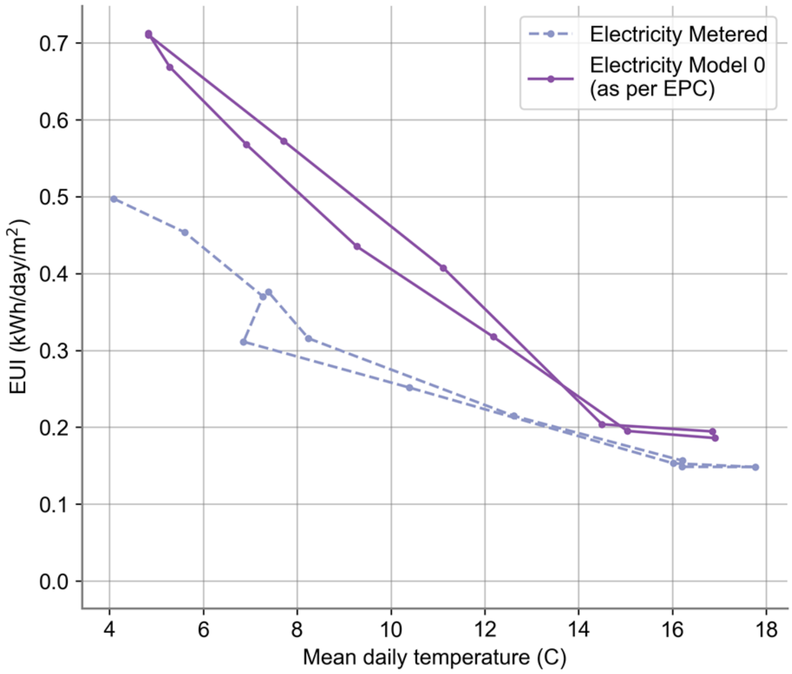

Figure 68 Monthly mean electricity energy use intensity against monthly mean temperature as metered and according to model 0 (as per the EPC).

Figure 69 shows the monthly average electricity energy use intensity in each month against the monthly mean external temperature for the metered energy and model scenario 4 (RdSAP9.94, actual weather, NEED updates, SERL occupancy updates). The discrepancy remains overall very similar to that for model 0 above. However, the modelled data for scenario 4 shows a clear drop in energy use in April, similar in shape to that observed for the metered data. The reduction in EUI is greater in the metered data than the modelled, the metered EUI drops by 0.059 kWh/day/m² between March and April, whereas the modelled EUI drops by only 0.052 kWh/day/m², or by 88% of the metered drop. This suggests that the impact of solar gains may be underestimated in the SAP model, although the scale of the discrepancy appears to be less than for gas heated homes.

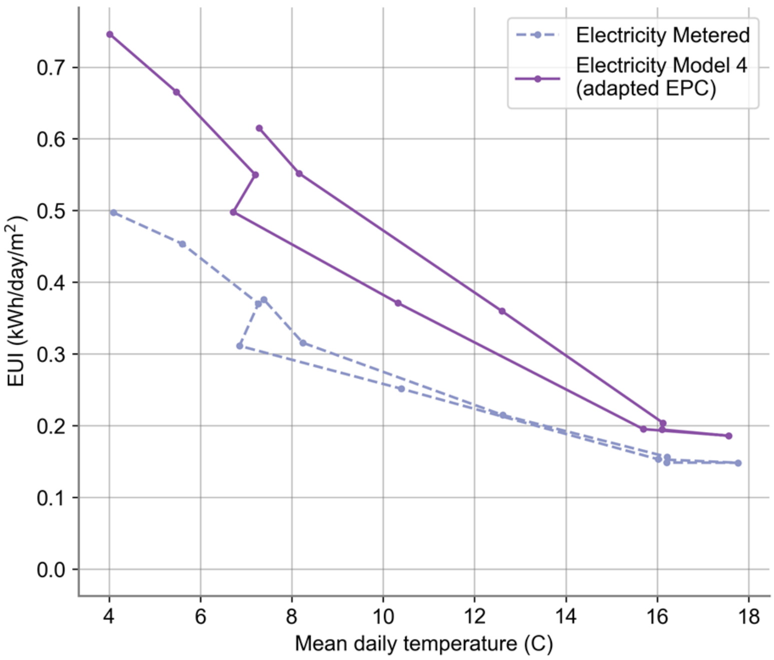

Figure 69 Monthly mean electricity energy use intensity against monthly mean temperature as metered and according to model 4 (fully adapted).

Energy signature analysis: whole sample results

Figure 70 shows the distribution of the HPLP (see the Methods section on the energy signature for an explanation of this and the following variables), the balance temperature and the base energy use intensity for the metered and modelled scenarios. For all parameters the distribution is clearly skewed as the mean does not coincide with the median.

The median HPLP decreases from model 0 to model 4 and the metered median HPLP is much lower than all the modelled medians. However, the mean is very similar across all cases. Analysis of a greater number of cases would be helpful to understand the reasons for this and increase the statistical power of the results. Both the mean and median are much lower for these electrically heated homes than the gas homes, the means are 2.3 W/m²K and 3.3 W/m²K for electrically and gas heated homes respectively. This is likely associated with the high prevalence of flats in the electrically heated sample.

Comparing the modelled results, the decrease in median HPLP for model 2 compared to models 0 and 1 is likely associated with the increased solar gains in the actual weather compared to the standard SAP assumptions as shown in Figure 68 above, this will tend to produce a lower gradient in the best fit line in the heating season. There is no significant reduction in median HPLP moving from model 2 to model 3, this is associated with the improved fabric and heating system efficiencies captured by the NEED data. The majority of the measures captured in the NEED data are for gas boiler upgrades and so are not applicable to this electrically heated group of homes. Less than 5 of the homes in the sampled used for this analysis received a measure under NEED so this makes very little difference to the average modelled results. The HPLP is very similar for models 3 and 4, this is expected because the changes to the occupant number and zone 1 demand temperature introduced in model 4 would have little impact on the HPLP. Moreover, very few of the homes in this analysis had a thermostat setpoint in the SERL data, possibly because some electric heating systems are less likely to have central thermostatic control.

The balance temperature is lower for the metered data than any of the modelled scenarios, and the spread is also much greater (this pattern is similar to that observed for gas heating). The SAP model assumes that heating is consistently used between October and May, but in practice households will switch on the heating at variable times, resulting in the much larger spread in balance temperatures observed for the metered case. Moreover, the balance temperature is much lower than any of the modelled scenarios, suggesting that typically heating is used for fewer months than is anticipated by the SAP model. The mean metered balance temperature is 11.3ºC, whereas for gas heated homes it was 13.6ºC. It is expected that the balance temperature would be lower for these homes because the HPLP was also lower. The balance temperature is similar and remains within error bars for all model scenarios. Note that contrary to the gas results, the spread in balance temperatures increases for models 2-4. The balance temperature also has implications related to the internal temperature, which is discussed later.

Finally, the base EUI is fairly similar across the modelled scenarios and remains within error bars but slightly increases for models 2-4. Model 4 incorporates the actual occupant number which would be expected to affect the base EUI significantly. The metered base EUI is smaller than modelled EUI for all scenarios, and the spread is much greater. This reflects that the SAP model is normative whereas actual energy use in homes is highly variable.

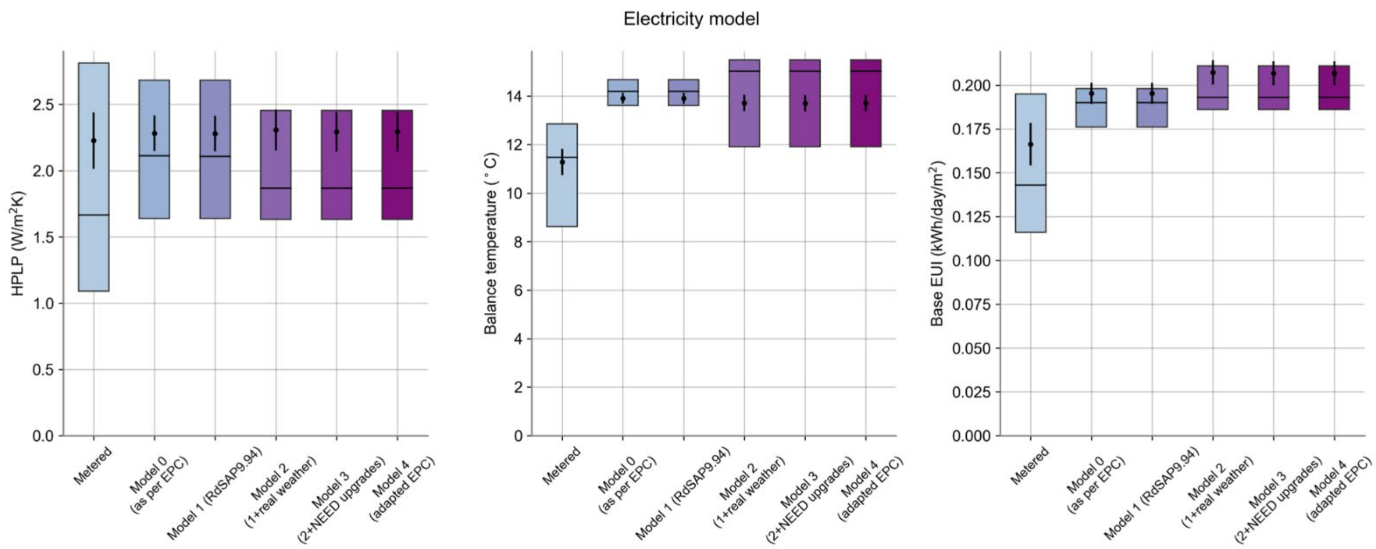

Figure 70 Distributions of PTG analysis parameters for the whole sample: HPLP, balance temperature and base EUI from left to right. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively.

Energy signature analysis: contextual variable results

We have analysed the energy signature parameters by EPC band and by the type of electric heating. We were unable to break this analysis down by as many parameters as for the gas heated homes because the sample was much smaller resulting in very small numbers of homes within individual categories.

Figure 71 below shows how the total base energy use intensity varies by EPC band for each of the scenarios. Note that homes which would move EPC bands under different modelling scenarios remain classified under the original scenario EPC-band for this and the following analysis. For EPC band D the metered base EUI remains lower than all modelled for all scenarios. However, it is difficult to draw firm conclusions about any trends for this parameter as sample size is small and the error bars are large.

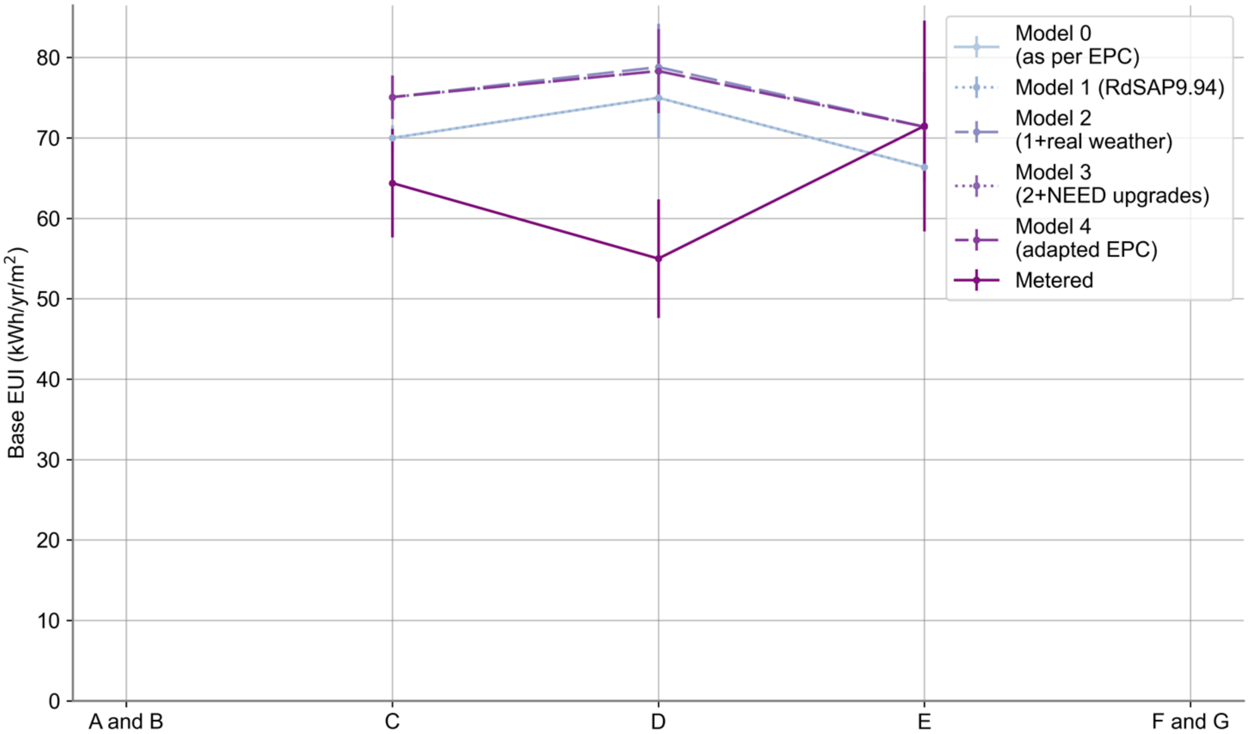

Figure 71 Average total baseline EUI (summer EUI) for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively.

Figure 72 below shows the metered and modelled HPLP for different EPC bands under different modelling scenarios. The error bars for the metered case overlap with those for the modelled scenarios in all cases for this parameter, meaning that no firm conclusions can be reached about the differences. However, the metered HPLP is slightly larger for band C homes than modelled, and lower for band D and E homes. This is similar to the pattern observed for gas heated homes and could suggest that heat loss may be overestimated in poorly rated electrically heated properties as well. However, a greater sample size would be needed to explore this further and with greater certainty.

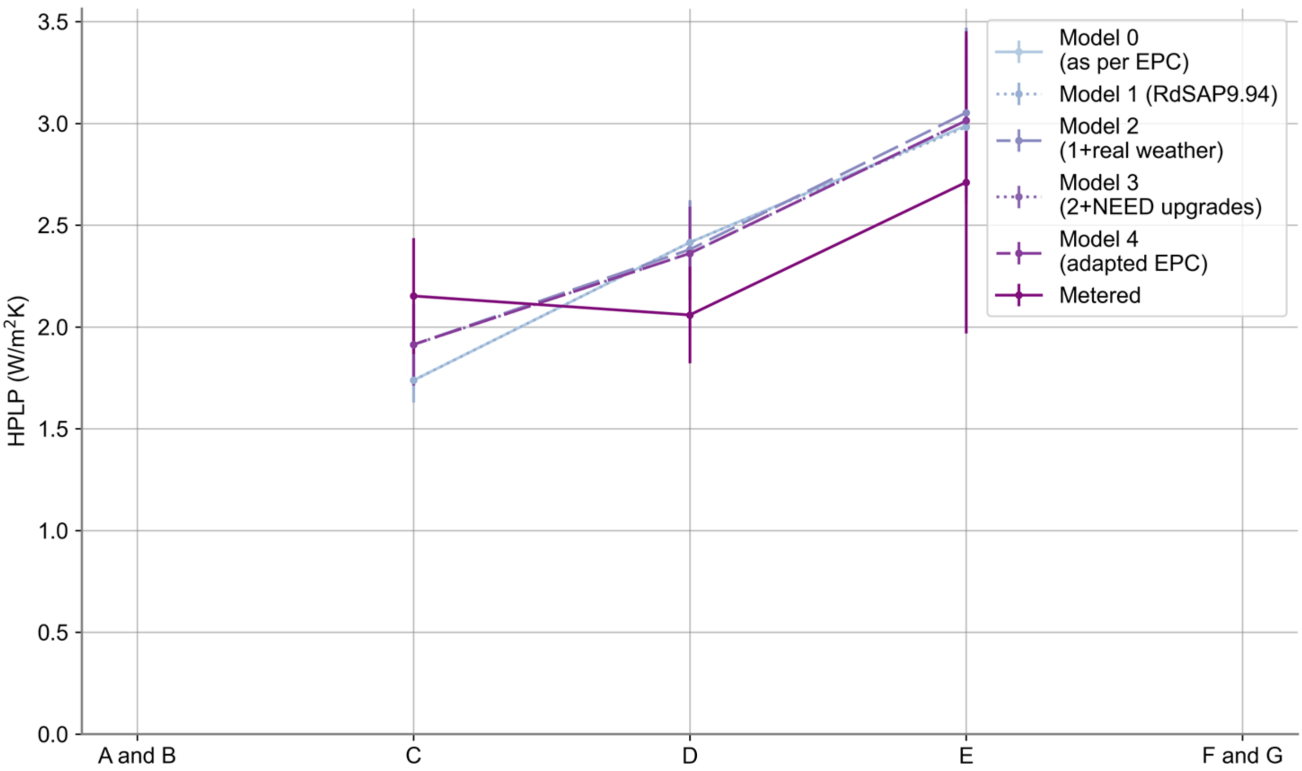

Figure 72 Average HPLP for EPC bands under different modelling scenarios and for the smart metered data. Points and bars represent the mean and standard error respectively. Note that model 3 and model 4 are extremely similar so difficult to distinguish.

Figure 73 below shows the distribution of HPLP for homes with different electric heating types as metered and under models 0 and 4. Again, analysis of these categories is tentative because the sample sizes are small and the standard errors are large compared to the differences between groups. Nonetheless, there appear to be separate issues for storage heaters compared to panel radiators. The mean and median metered HPLP for homes with storage heaters is lower than the modelled value. However, the mean metered HPLP for homes with panel radiators is larger than the modelled values, but the median is lower. The distribution is highly skewed for this category of homes and it would be beneficial to analyse a greater number of homes to understand in greater detail the particular issues for this group.

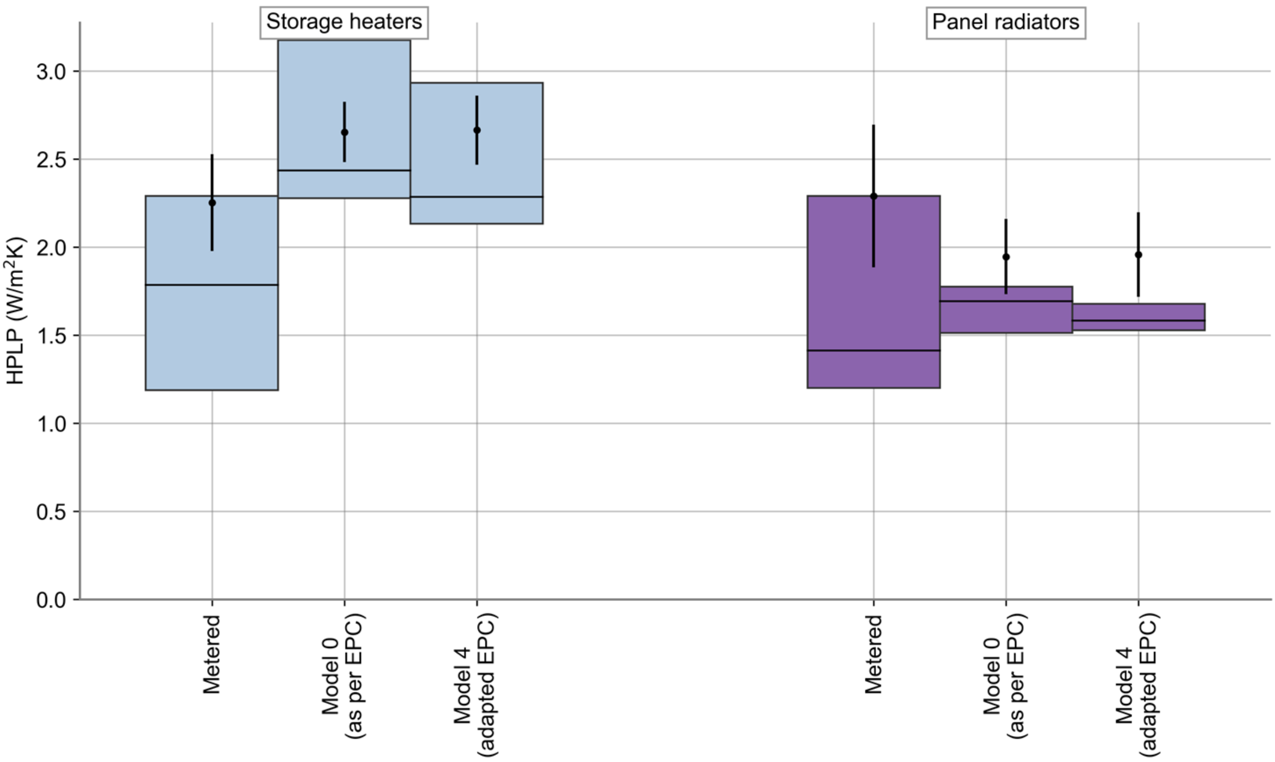

Figure 73 Distributions of HPLP for electric heating types. Boxes are bound by the 25th and 75th percentile, and the middle bar represents the median. Points and bars represent the mean and standard error respectively, note that for some groups the standard error is smaller than the size of the point.

SAP modelled Mean Internal Temperature (MIT) compared to metered MIT with both EPC-EER banding and Heat Loss Parameter (HLP)

This section presents the results of the analysis performed on the EFUS Measured Internal Temperatures and the comparison to NBM-SAP Modelled internal temperatures for the subsample of EFUS homes that are represented in both EFUS and NBM-SAP.

Although there are 70 dwellings in EFUS with temperature data and electric heating, more than half of these dwellings are not represented within NBM-SAP. This meant that after cleaning (performed as described in the methods section of Part 1), only 31 dwellings were available for comparison of Measured and Modelled temperatures. Due to this small sample, it is recommended that these statistics be read as indicative rather than conclusive, especially where dwellings have been grouped into smaller categories.

In the process of analysing electrically heated properties, it was observed that there exists a systematic difference between SAP ratings calculated by EFUS[74], and those calculated by

[74] EFUS is a sub-set of EHS properties these are all surveyed by an EHS surveyor who collects data that BRE then convert into SAP input parameters. Note, this process is different from the process used by commercial EPC assessors.

NBM-SAP[75], with NBM-SAP consistently rating electrically heated dwellings more favourably. For this analysis, rather than the SAP rating being drawn from the NBM data along with the modelled temperatures, the SAP rating is drawn from the EFUS dataset. Since the NBM-SAP temperature calculation is unaffected by cost, this was thought to be the best approach.

Summary of temperatures

Figure 74 shows the distribution of mean monthly temperatures in the Modelled and Measured samples, for the heating season, for electrically heated dwellings.

Electrically heated dwellings are modelled to be 0.5°C warmer than measured. This is the reverse of what is observed in gas heated homes where they are modelled to be 1.4°C colder. It is only in the non-living areas (rest of house i.e. Zone 2) that electrically heated homes are measured to be warmer than modelled.

Furthermore, for the gas heated homes there was little difference (less than 0.3°C) in measured temperature between Z1, Z2, and whole dwelling, whereas in the electrically heated sample, there is a difference (greater the 1°C) in measured temperatures between Z1, Z2, and whole dwelling which suggests that electrically heated dwellings are ‘zoned’ in a way that gas heated homes are not. This could be because gas heated homes are predominately centrally heated and controlled whereas electric heating systems consist of independent room heaters not centrally controlled.[76]

A final feature to note is that the modelled temperatures are much more tightly clustered around the median than the measured temperatures. This may be predominantly attributable to the standardised occupancy assumptions in the model, including their relationship to internal heat gains and heating schedules. It is also possible that the range of control strategies available within the model is not sufficient to describe the operation of electrically heated systems, resulting in greater variability than the model assumes, or that the thermal inertia of this group of dwellings is particularly poorly represented in the model.

[75] NBM-SAP uses the same EHS SAP data inputs but calculates the SAP outputs using a different software implementation of SAP i.e. NBM.
[76] Note, heat pumps have been excluded from analysis in this report.

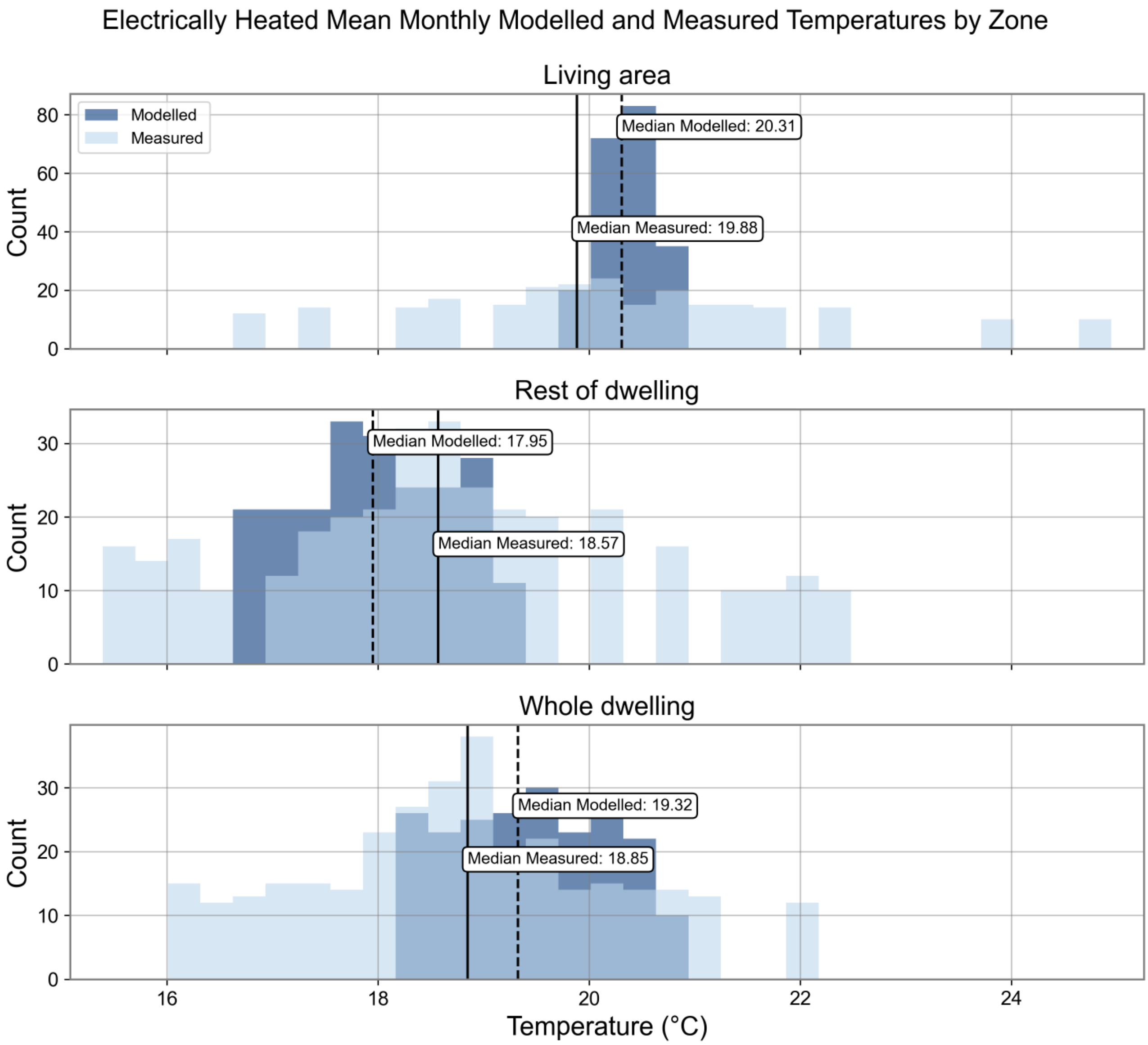

Figure 74 Histograms showing the distribution of monthly heating season Mean Internal Temperatures for electrically heated dwellings, split by zone. Note that as before, bins with fewer than 10 measurements have been excluded in order to comply with Statistical Disclosure Control.

SAP predicts a bigger temperature difference between zones the more sophisticated the controls. Control Type 1 is the simplest controls and has the smallest predicted temperature difference between zones, whereas Control Type 3, the most sophisticated, is SAP modelled to have a maximum difference between zones of 3°C and HLP of 6W/m²K. There are no Control Type 1 dwellings in the monitored electric sample, which have the smallest modelled Z1-Z2 temperature difference.

Finally, there are additional features of the electrically heated sample that may account for the behaviour of the model for these homes compared to the behaviour of the model across the whole stock, including that there are proportionately more flats which may have a more even distribution of space between Z1 and Z2, and potential difference in occupant characteristics and behaviours compared to the whole population.

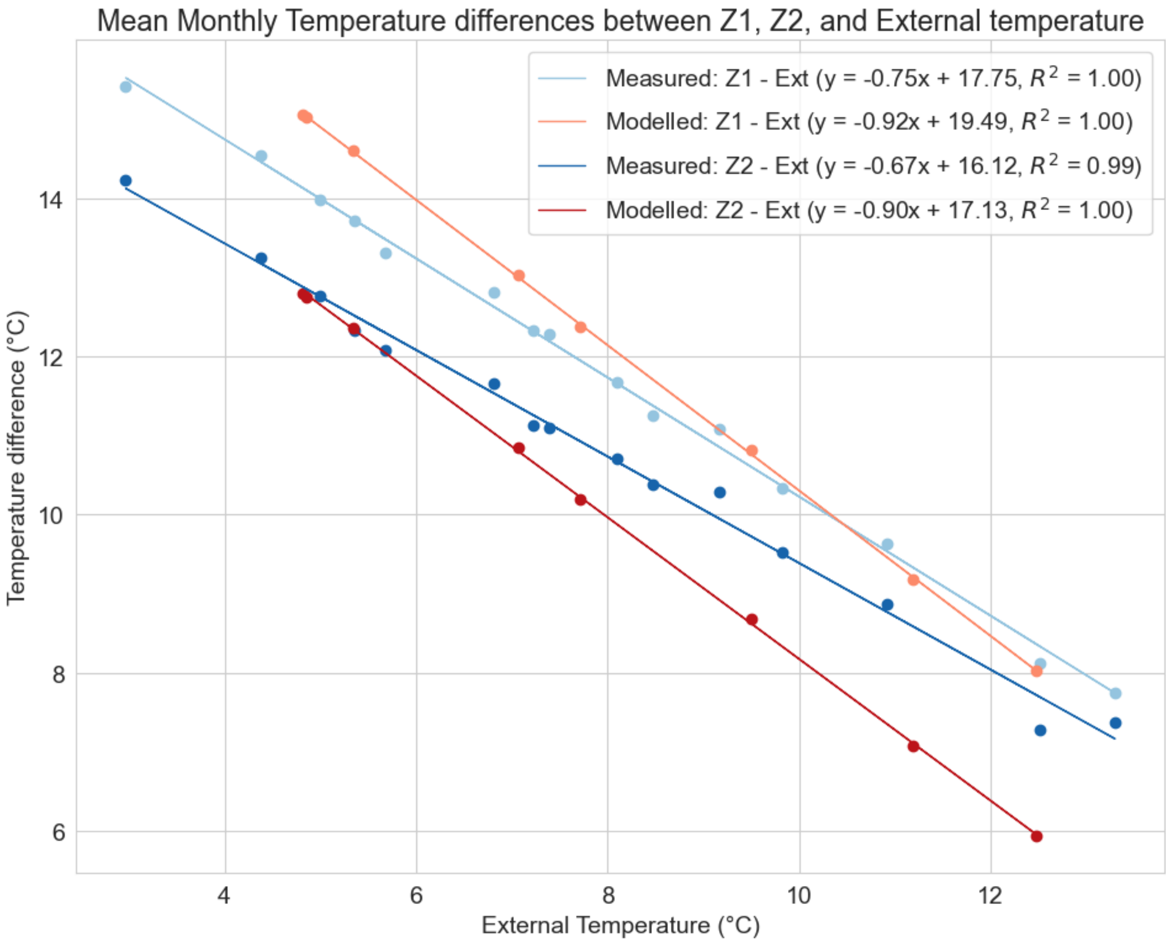

Figure 75 Linear regression for mean monthly temperature difference between indoors and outdoors versus external temperature, for Modelled and Measured data during the heating season for electrically heated dwellings.

Figure 75 shows the relationship between the temperature difference between indoors and outdoors, and the external temperature for different zones as modelled by SAP and as measured. Modelled data is shown in two shades of red, and Measured data is shown with two shades of blue. The relationship between Z1 and Z2 in the measured data is different to that shown in the gas heated sample. Whereas for gas heated homes the measured data showed no significant difference between Z1 and Z2 in terms of their relationship to external temperature, within the electrically heated sample the model predicts a slightly stronger inverse relationship to external temperature than is observed in the measured sample, and the intercepts suggest that the model overpredicts indoor-outdoor temperature differences compared to the measured data.

The measured slopes are also more divergent in the electrically heated sample than the gas sample, however the measured slopes are less steep than modelled. Similarly to the gas heated sample, the model is overestimating the difference between Z1 and Z2 temperatures compared with measured, although this is more pronounced at higher outdoor temperatures. At very low temperatures, the model may overestimate the indoor-outdoor temperature differences, suggesting that the model predicts higher internal temperatures at very cold outdoor conditions than are measured in the case of electrically heated dwellings (whereas in the case of gas heated dwellings, the indoor temperatures are maintained at a stable level regardless of the external temperatures). There are multiple potential reasons for this, including the relative cost of electricity compared to gas, characteristics of electric heating systems such as thermal storage, or different occupant practices associated with electric systems, and the construction types of these dwellings. Two further possible issues are that electrically heated dwellings could have different heating schedules to gas systems, which might make the scheduling assumptions in Table 9 of SAP 2012 V9.92 especially inappropriate for electrically heated dwellings, and that the heating systems may not be as responsive to colder temperatures as gas systems (potentially due to features like a lack of modulation capability, high thermal inertia) or have the same operative thermal comfort profile as SAP expects..

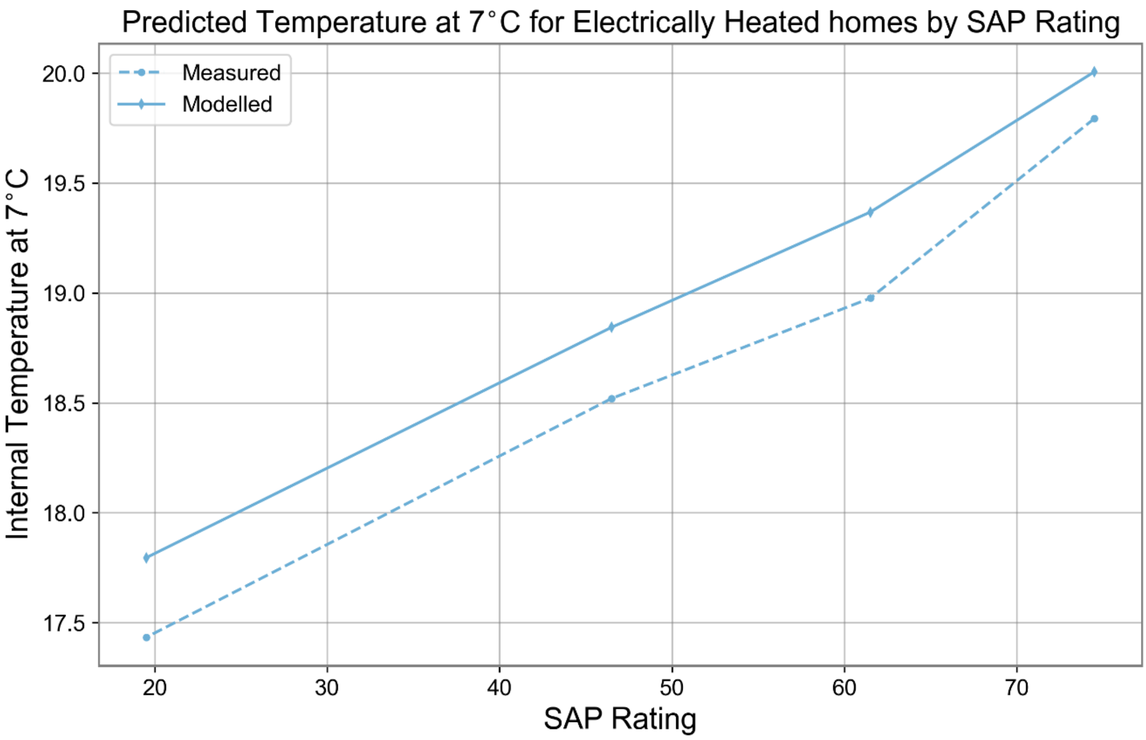

Figure 76 Predicted Mean Internal Temperatures for Modelled and Measured data, differentiated by the SAP Rating, for an external temperature of 7°C. Predictions are based on a linear regression of mean monthly internal temperatures against mean monthly external temperatures for the heating season.

Table 18 Number of EFUS electrically heated dwellings in each SAP Rating Band used in the analysis.

SAP Rating Band	Number of dwellings
A&B	0
C	10
D	8
E	5
F&G	8

Figure 76 shows that after correcting for the effect of external temperature, the model seems to overestimate the MIT of electrically heated homes compared with measured data. This is contrary to results for the gas heated sample, although should be treated as indicative due to the small number of dwellings in each band (see Table 18).

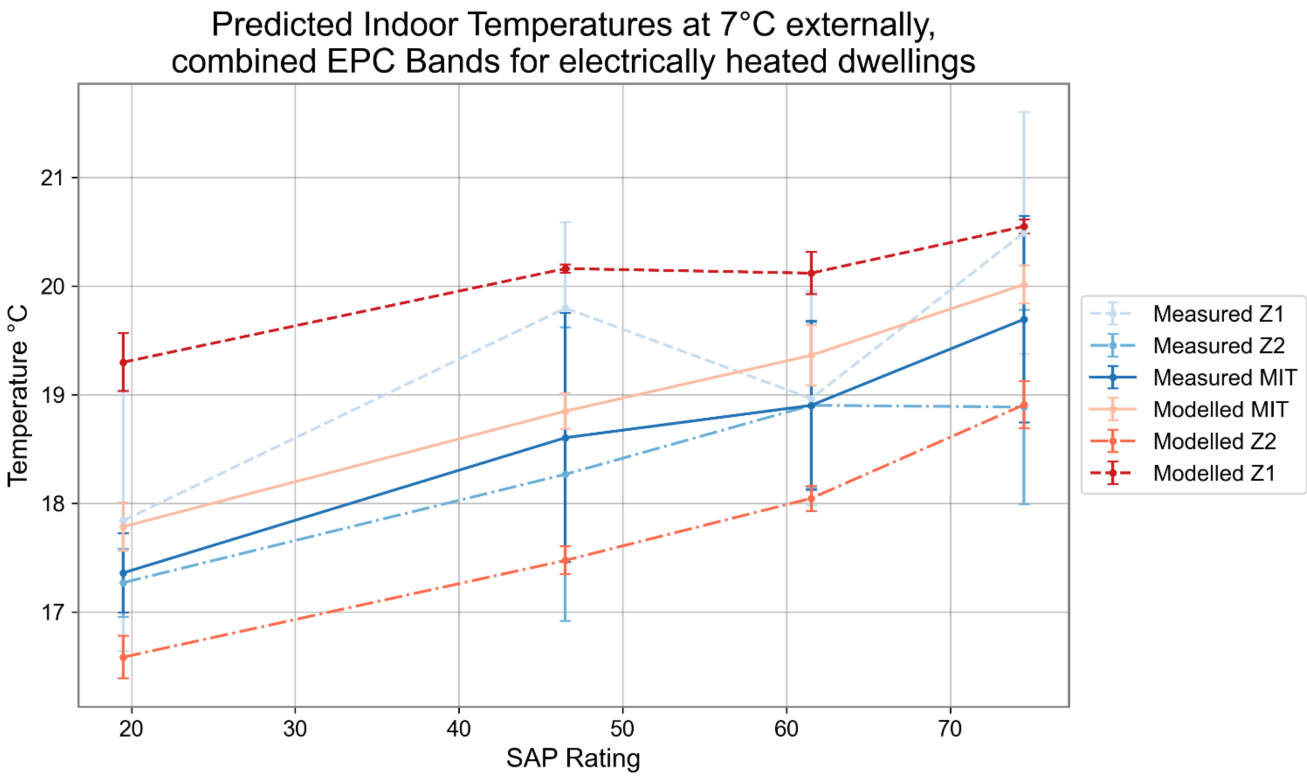

Figure 77 Predicted indoor temperatures for modelled and measured data, differentiated by the SAP Rating and dwelling zone. Error bars show the standard error on the mean.

Figure 77 shows that as with the gas heated sample, the least efficient properties are the coolest for all zones. There may also be a temperature difference between different zones in the dwellings for the Measured sample, Z1 being the warmest and the Z2 being coolest. Interestingly, there is an apparently larger difference between the Z1 and the Z2 temperatures for the most efficient properties than the least efficient in the Measured data, which could suggest this difference is driven by the preferences of occupants or the presence of more sophisticated controls, although a greater sample size would be needed to draw firm conclusions. The modelled data is distinct in that as with the raw temperature distributions, there is a large difference in temperature between Z1 and Z2. Indeed, for band F&G, the temperature difference between Z1 and Z2 is 2.7°C, whereas the measured data shows a smaller difference of 0.6°C between Z1 and Z2, although there is high uncertainty, especially for the measured data. The large difference in modelled temperature for each zone is potentially due to the presence of high Heat Loss Parameters for properties in bands F&G.

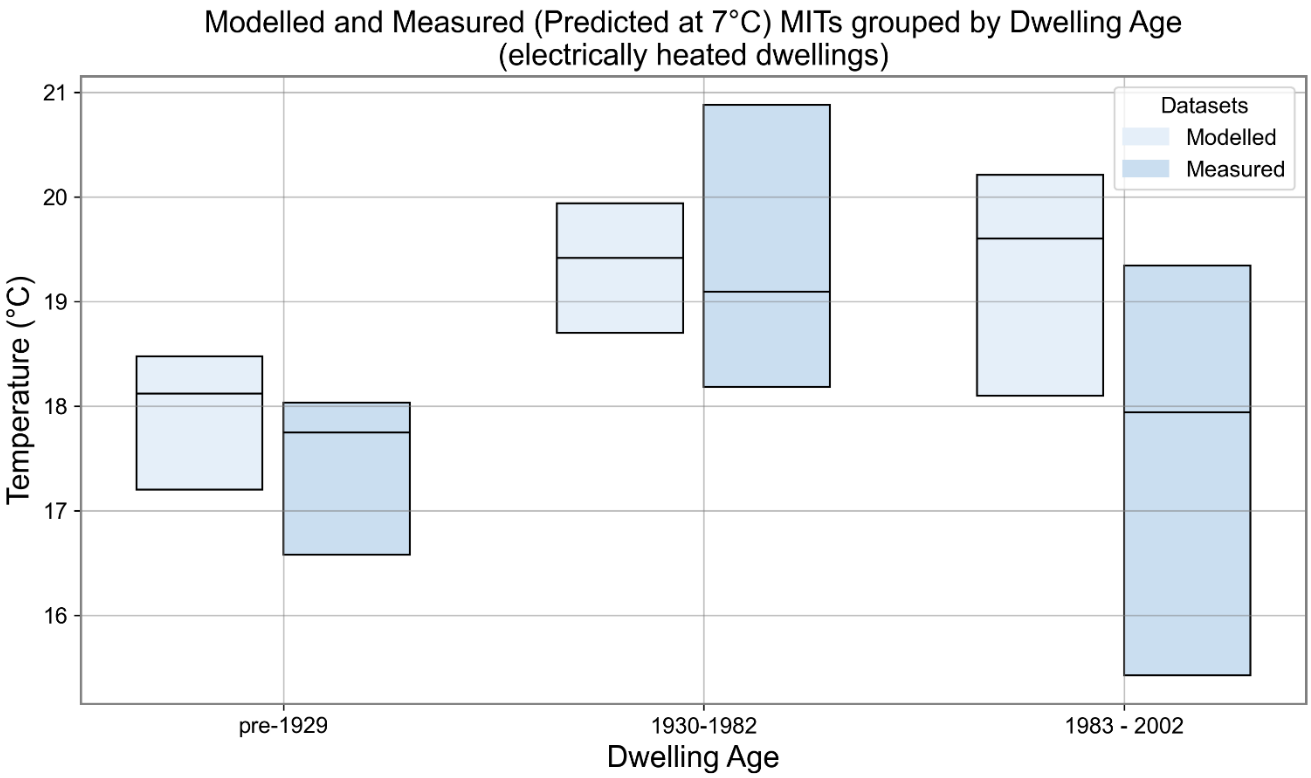

Figure 78 Box plot showing predicted internal temperatures for modelled and measured data, for an external temperature of 7°C, disaggregated by the age of the dwelling.

Figure 78 shows the distribution of predicted temperatures disaggregated by dwelling age, for modelled and measured data. Although all of these categories contain relatively few dwellings, the modelled data suggests that there is an upward trend in internal temperatures as dwellings become newer. However, this trend is not supported by measured data, with dwellings built post-1983 being cooler than those built between 1930 and 1982, and similar to those built pre-1929.

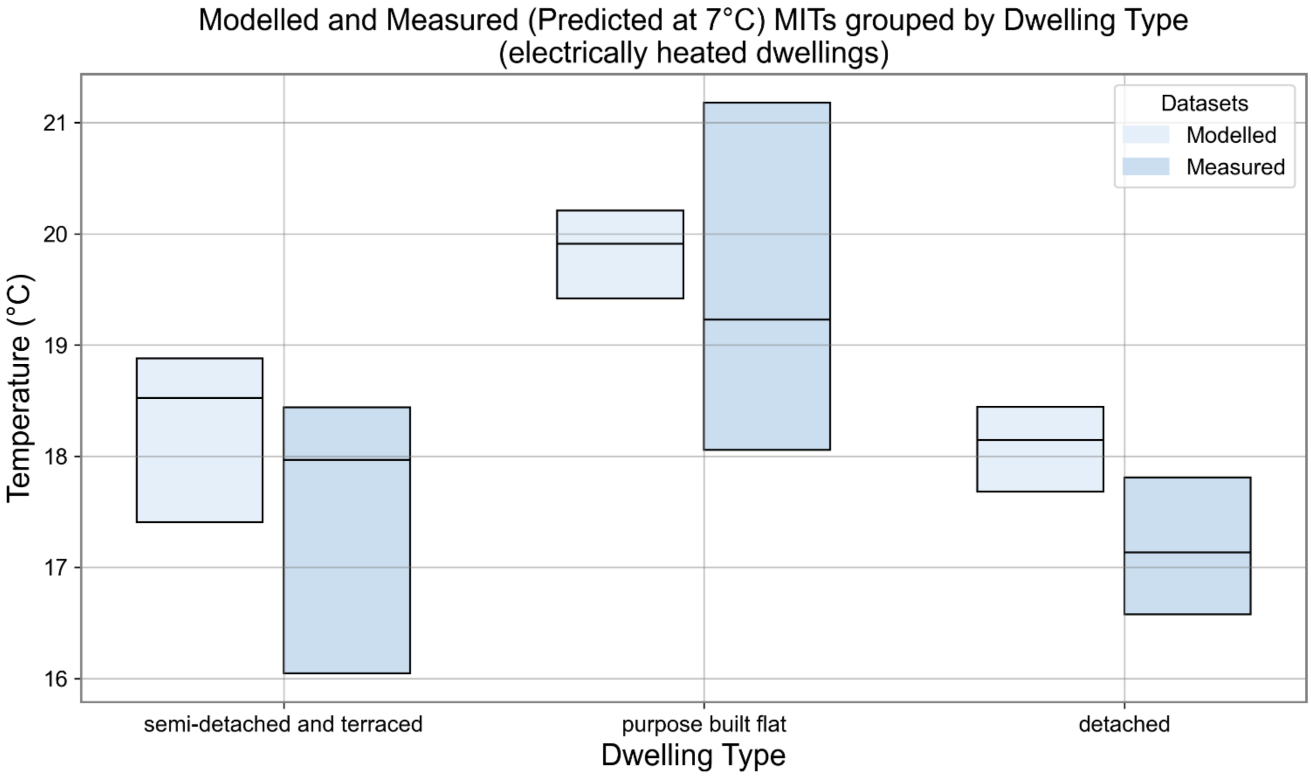

Figure 79 Box plot showing the disaggregation by dwelling type of predicted internal temperatures for modelled and measured data.

Figure 79 shows that predicted mean internal temperatures based on measured data are lower than the model predicts for all dwelling types. The gap between modelled and measured temperatures is particularly large for detached properties, and purpose-built flats maintain the highest temperatures. This could be a result of purpose-built flats being more likely to benefit from inter-dwelling heat gains than terraced or detached houses, although flats are typically smaller than detached properties, which may mean that they are more likely to be heated in their entirety than detached houses.

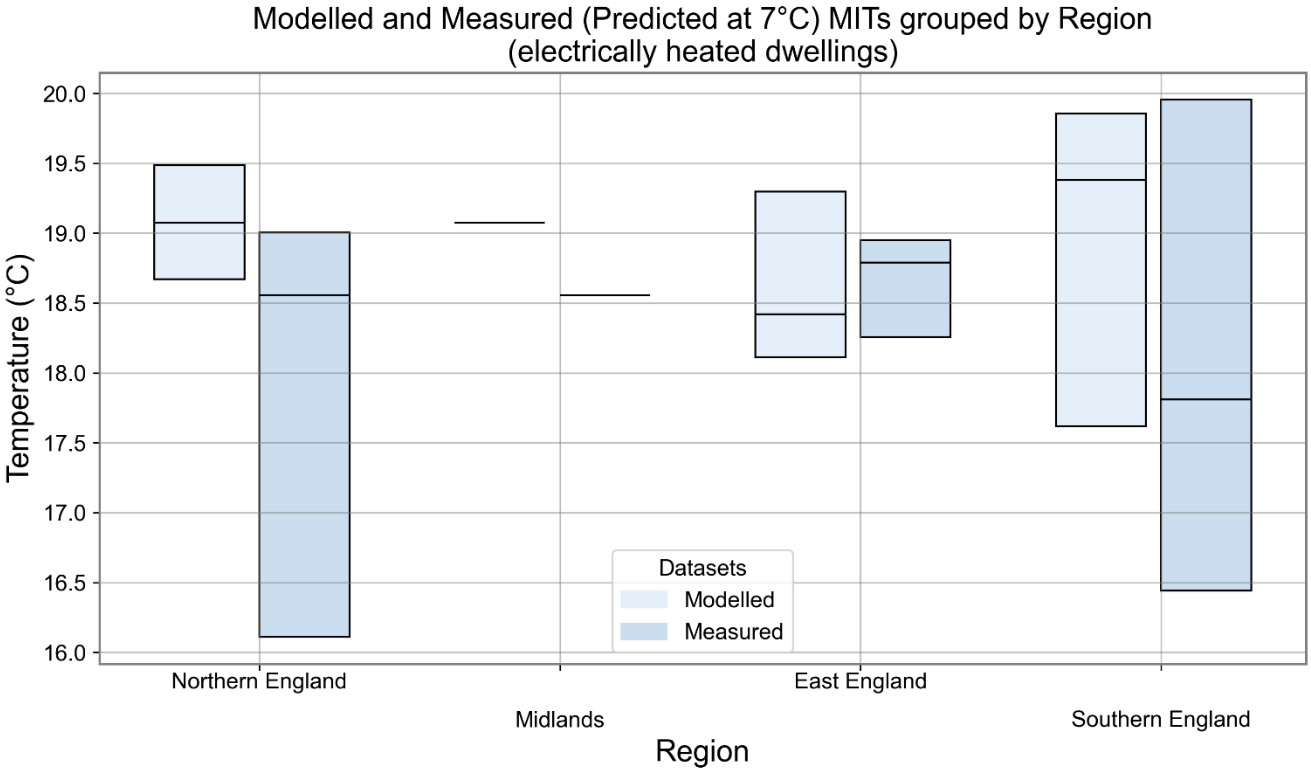

Figure 80 Predicted temperatures for the whole dwelling for modelled and measured data, disaggregated by geographical region. Where there is insufficient data to construct a box plot, only the mean of the available data is plotted, with modelled on the left and measured on the right.

Figure 80 is a box plot showing the regional disaggregation of predicted internal temperatures, for modelled and measured data. Note that there are 31 dwellings in total represented, and groups have been aggregated to achieve the maximal inclusion of data despite the plausible differences in dwellings and occupant characteristics between the North West and North East, and the South East and the South West. Where there is insufficient data to construct a box plot, only the mean of the available data is plotted, with modelled on the left and measured on the right.

Although the trend is weak, Figure 80 shows that predicted temperatures for the modelled data are warmer in Southern England than in the Midlands and East England, which is in line with expectations, however, the measured data indicates that dwellings in southern England are cooler (although with a large spread). This could be due to the inclusion of the south west of England within the category, which Annual Fuel Poverty Statistics in England showed to be the region with the highest fuel poverty gap in the UK, based on 2023 data[77].

[77] Annual Fuel Poverty Statistics in England, 2024 (2023 data): https://assets.publishing.service.gov.uk/media/65ccecba1d939500129466a9/annual-fuel-poverty-statistics-report-2024.pdf

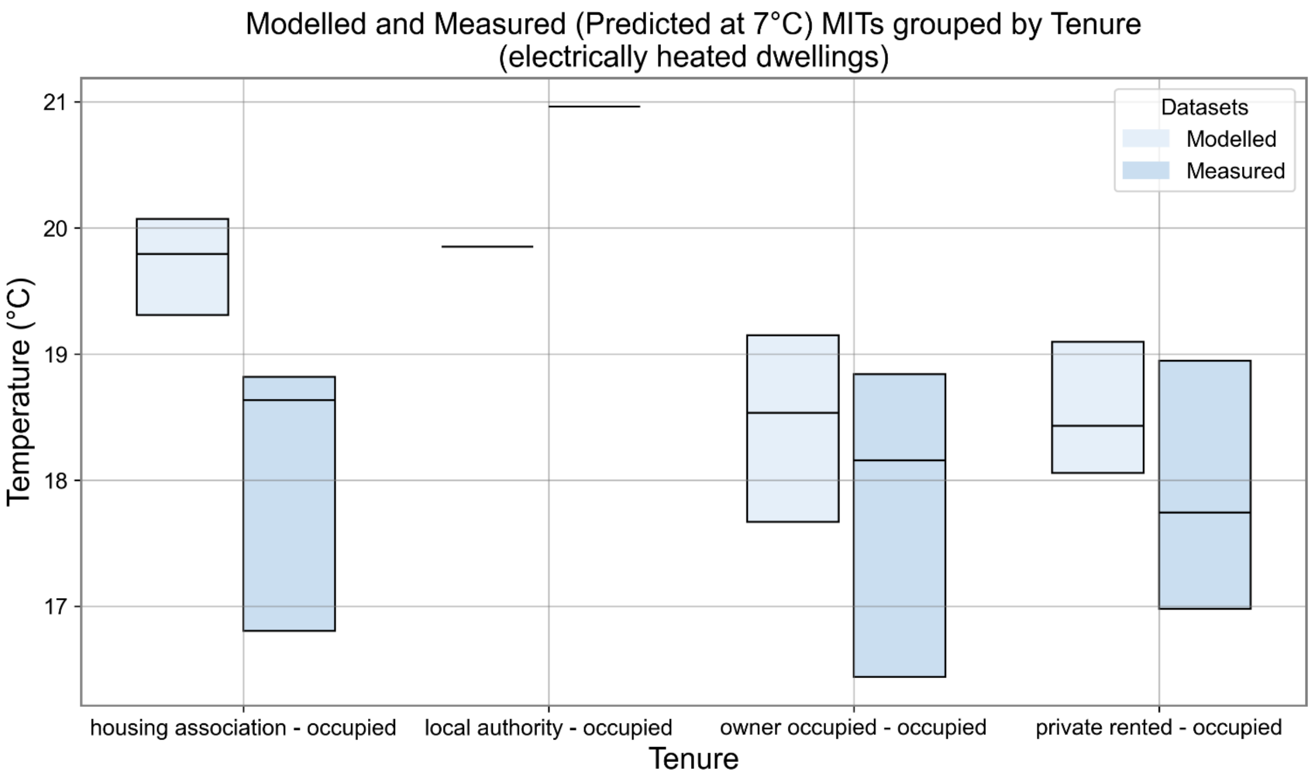

Figure 81 Box plot showing the disaggregation of predicted internal temperatures by tenure, for modelled and measured data. Where there is insufficient data to construct a box plot, only the mean of the available data is plotted, with modelled on the left and measured on the right.

Figure 81 suggests that housing association dwellings are almost a degree colder than the modelled data predicts, and that local authority dwellings may be warmer than NBM-SAP suggests. However the Local Authority results are based on just three homes.

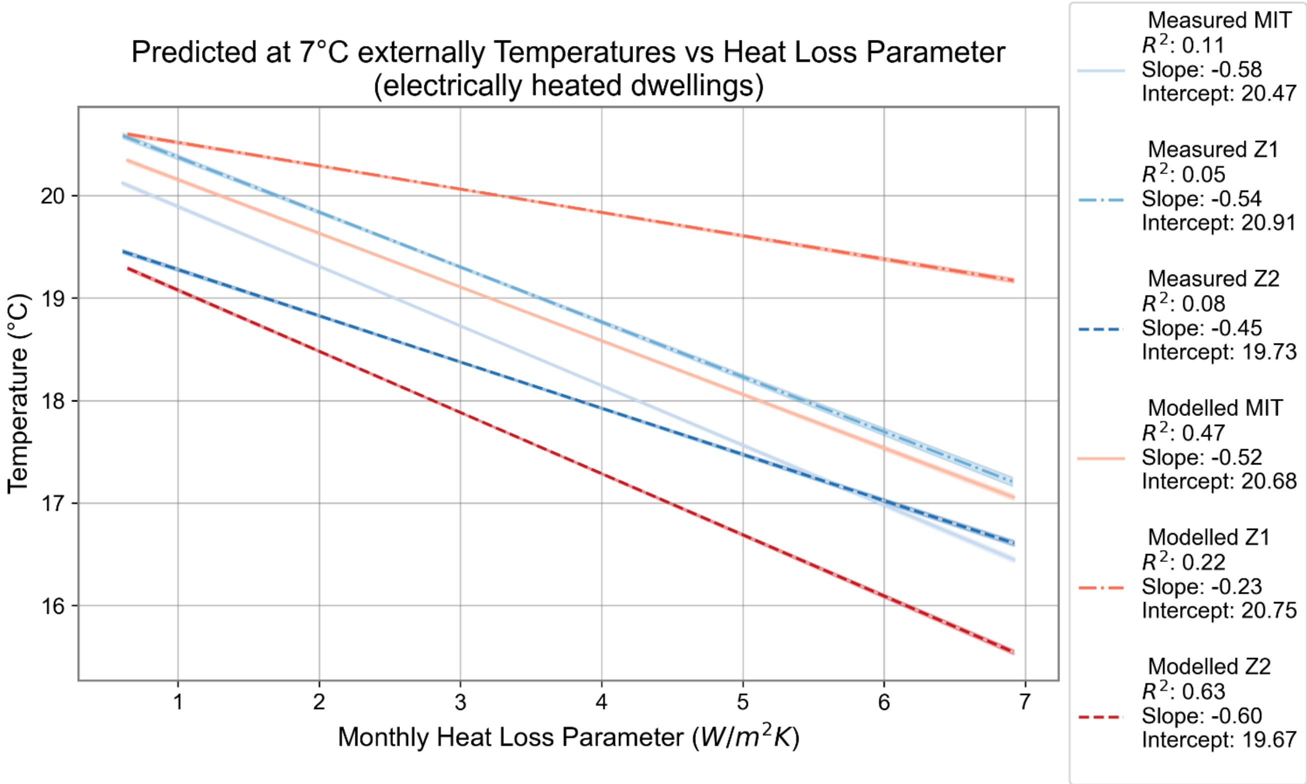

Figure 82 Regression plot showing the behaviour of predicted internal temperatures against the NBM-SAP modelled Monthly Heat Loss Parameter (HLP), for modelled and measured data for the whole dwelling, Z1 and Z2.

Figure 82 shows the relationship between Mean Monthly HLP and Predicted Internal Temperatures for Measured and Modelled data, for different dwelling zones. Firstly, the R^2 values suggest that the Monthly HLP is not a strong predictor of internal temperatures, except in the case of the Modelled Z2 temperatures, and to a slightly lesser extent, the Modelled MIT. This is to be expected due to the effect of SAP9.92 Table 9a, which imposes the Zone 2 temperature, on which the MIT rests, based on the HLP. In the case of the Measured data however, the NBM-SAP calculated HLP does not appear to have a significant relationship to predicted internal temperatures for any zone in terms of R^2.

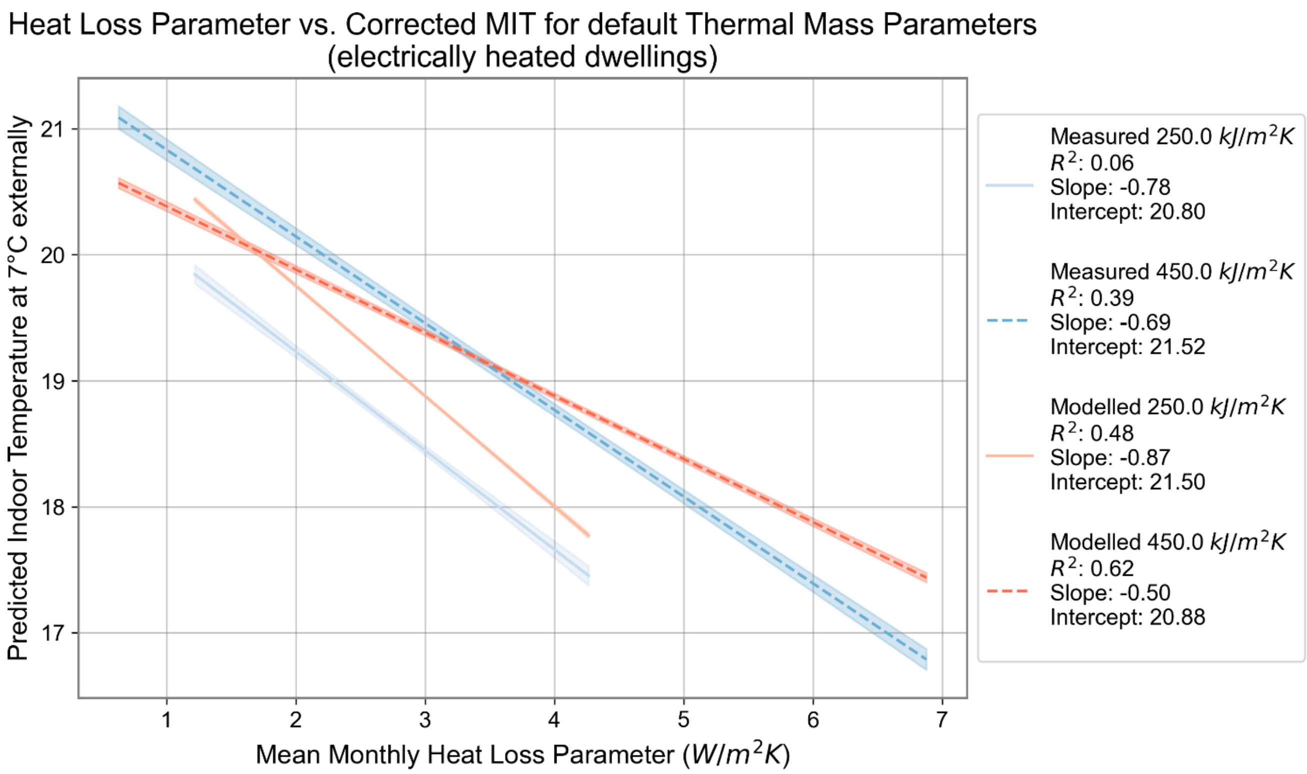

Figure 83 Linear Regressions of Predicted Indoor Temperatures against Mean Monthly Heat Loss Parameter for Measured data, disaggregated by Default Thermal Mass Parameters (TMPs).

As discussed in Part 1 of this report, the Thermal Mass Parameter (TMP) is used within SAP to calculate the utilisation factor and the temperature reduction when the heating is off. This means that buildings with different TMPs may be expected to show different relationships to Predicted Indoor Temperatures. Qualitatively, the negative slopes align with the physical system, in that as the dwellings HLP goes up, the predicted indoor temperatures go down, and buildings in the higher thermal mass category have a higher intercept which indicates better heat retention.

Figure 83 also shows that for the Measured data, the R^2 value for the heavyweight building (R^2=0.39) is higher than that of the mediumweight building (R^2=0.06). This suggests that there may be a moderate relationship between HLP and predicted temperature for the heavyweight category but not the mediumweight category. For the Modelled data R^2 value for the heavyweight building (R^2=0.62) is also higher than that of the mediumweight building (R^2=0.48) although not so dramatically. Noting again that this should be treated with caution, as there are only 8 dwellings in the heavyweight category and 22 in the lightweight category.

The plot also shows that in the measured temperature in mediumweight buildings, indoor temperatures decrease less sharply with increasing HLP than the model predicts, suggesting that the model may be either attributing too large an effect to the HLP, or under-accounting for variables related to occupancy compared to the measured data. In the case of the heavyweight building, the effect is reversed, with the Modelled data less sensitive than the Measured to the monthly HLP (although with only 8 dwellings, this interpretation is highly speculative). Another way to look at this plot is that in the case of the Measured data, the slopes for both categories are very similar, which suggests that they have the same response to monthly HLP, although the heavyweight buildings have a higher y intercept (indicating they are warmer).

Forensic results

Figure 84 compares the Energy Efficiency Rating (EER) that were generated using RdSAP and lodged in the EPC registry for 4 forensic resurveyed electrically heated homes, compared against the EER generated from a new full SAP calculation. For comparison, the gas-heated homes are also included. The electrically heated homes show a larger difference between the original and new EER, with three out of the four homes having a worse EER when re-surveyed, the opposite to most gas heated homes. Interpreting data for such a small sample is risky, however, the data suggests the performance gap may increase following a more recent full-SAP survey for electrically heated homes.

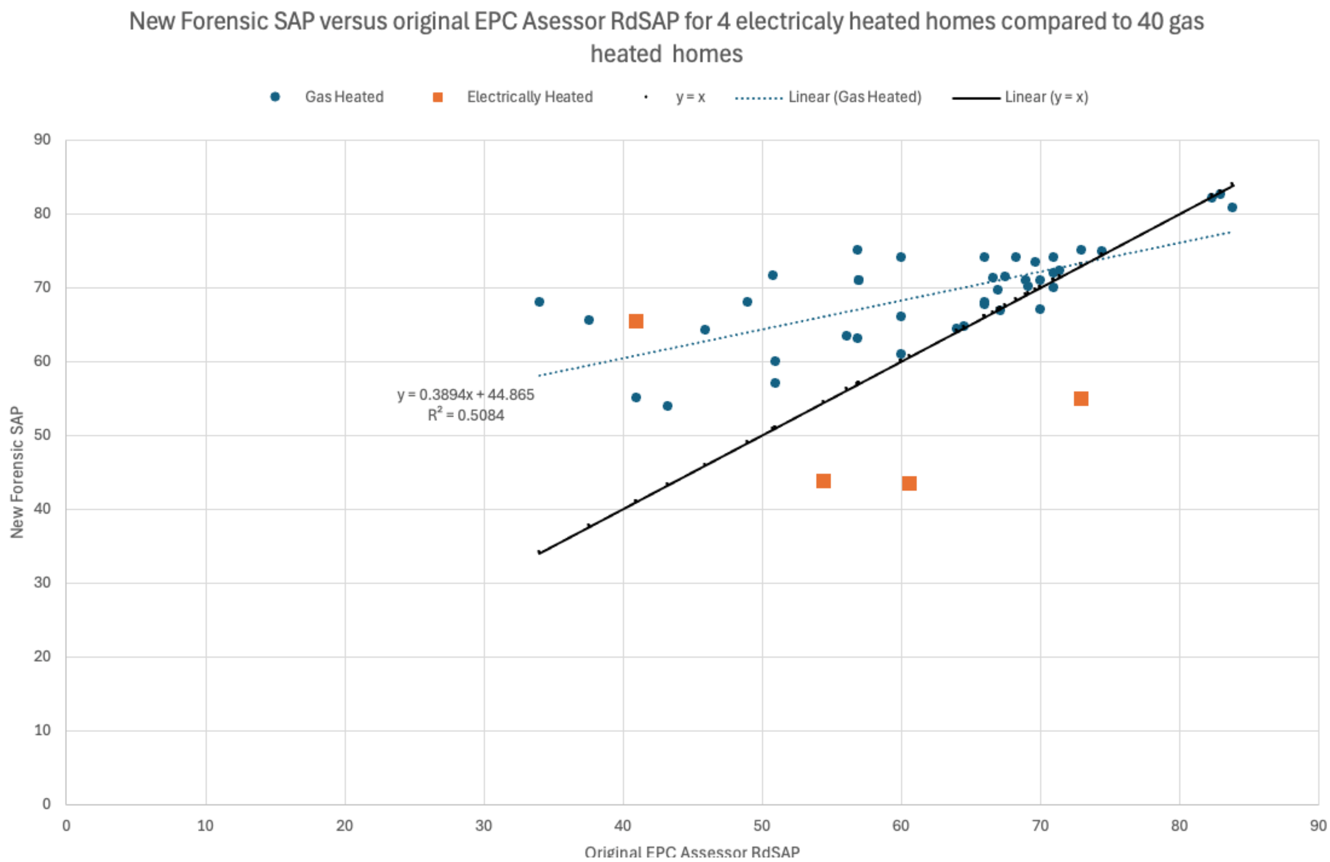

Figure 84 Comparison of EER score between assessment via full SAP from an expert EPC assessor and the existing EER from a commercial EPC rating for the same building.

Figure 85 compares the original (Commercial RdSAP) performance gap (% difference between modelled and measured total primary energy intensity) with the new gap (Expert SAP) using the forensic full SAP survey results. Clearly the sample size is very small, however the discrepancy remains similar between the two groups of results.

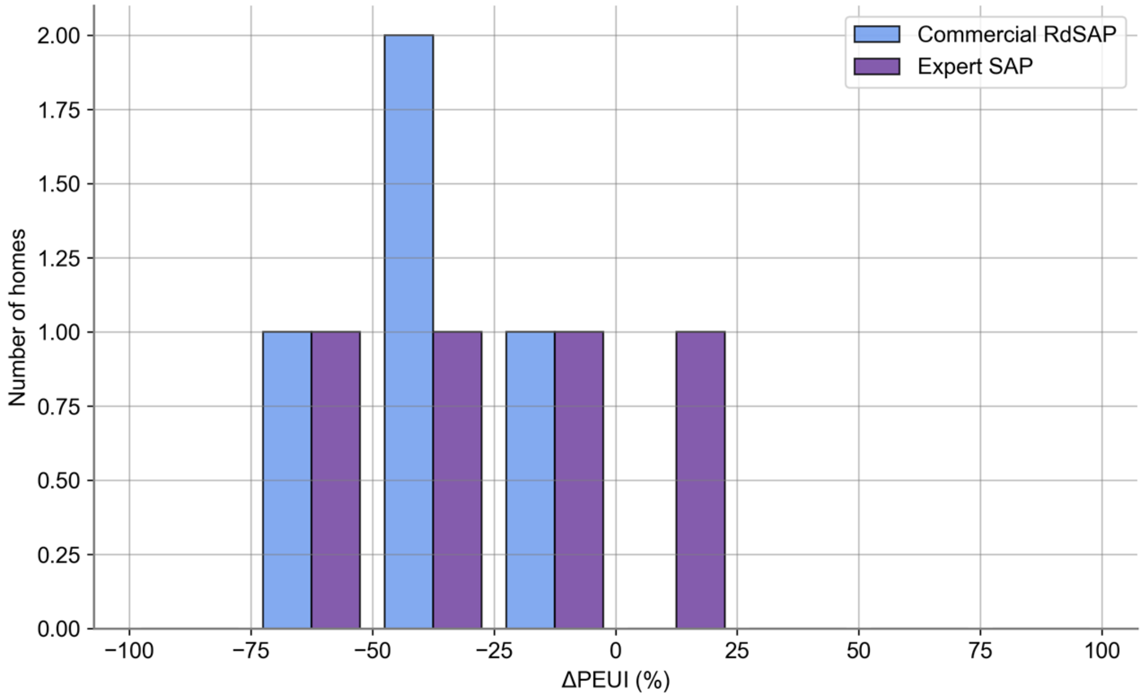

Figure 85 The percentage difference in primary energy use intensity between the metered energy use and modelled energy use for homes assessed by an expert EPC assessor and their previous commercial EPC assessment.

To help identify the main cause of this reduction in the gap, the impact of each change to the calculation was calculated for each of the forensic sites. The majority of these individual changes resulted in less than 1 EER point difference. Changes have been classified as one of the following:

- Measures installed since original EPC
- Assessor error
- RdSAP core process and conventions

Figure 86 shows the average percentage variation caused by these different categories for comparison, data from 4 electrically heated homes is compared against the 41 gas heated homes. Data for individual properties (Figure 87) shows a very large variation in percentage change due to each of the three categories. The four homes on the right of the diagram (plotted with circular data points) are electrically heated homes.

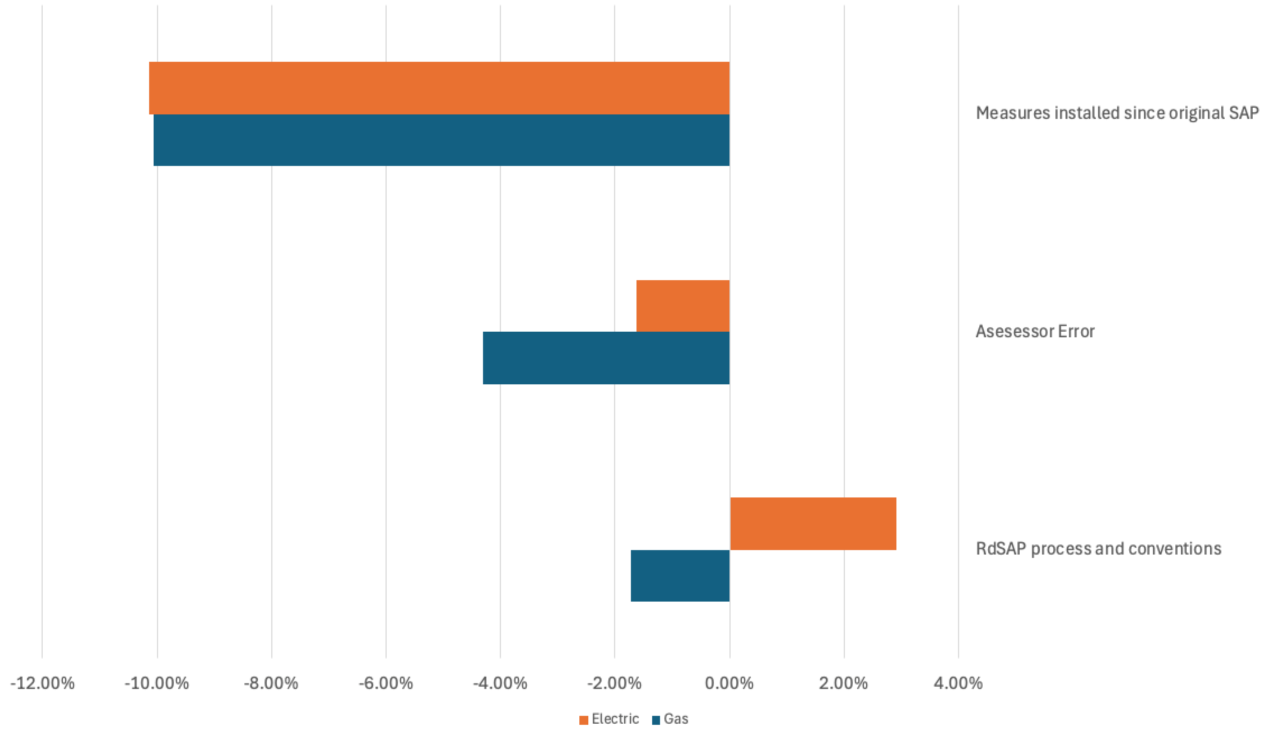

Figure 86 Average percentage change in space and hot water energy use from commercial EPC assessment to expert EPC assessment for gas and electric homes.

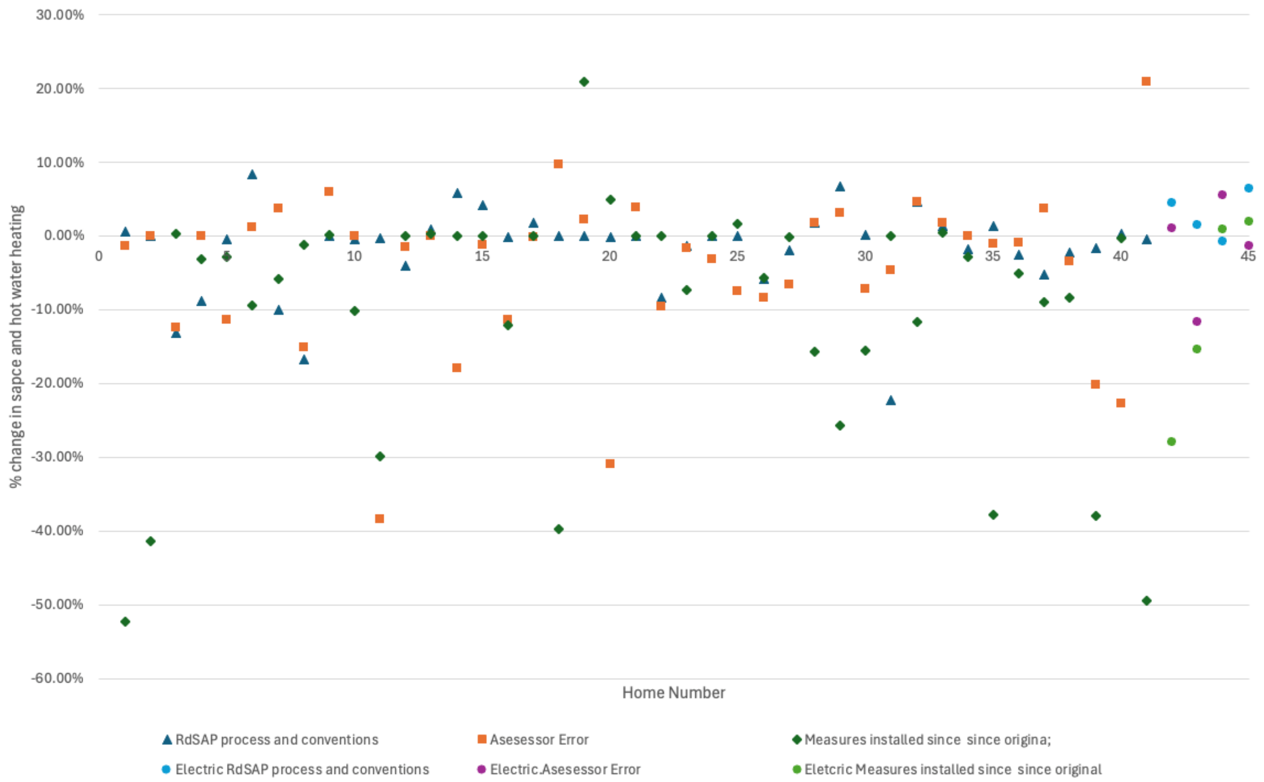

Figure 87 Percentage change in space and hot water heating between commercial and expert EPC assessment from different categories for 40 homes.

Table 19 lists the changes that resulted in greater than 5% change in total heating energy use. For electrically heated homes there is no consistent cause of major changes to the heating energy use, unlike gas heating where boiler upgrade after original EPC survey is a key change.[78]

Table 19 Changes from commercial to expert EPC assessment that resulted in greater than 5% change in total heating energy use for electrically heated homes.

Site	Classification of change	Change	SAP EER	EER change	% SAP EER change	Space heating (kWh/a)	Hot water (kWh/a)	Total heating (kWh/a)	% Total heating change
E5	RdSAP core processes	Sloping ceiling areas ignored by RdSAP	37.7	3.3	-8.1%	8507	2204	10711	7.0%
E6	RdSAP core processes	The measured living area is 26.6m2 which is greater than the RdSAP default of 12.88m2 used in the EPC	54.5	2.1	-3.8%	6919	2511	9430	5.6%
E1	Assessor errors	Wrong age band selected by assessor (wall U-value should have been 0.35 rather than 0.30, floor insulation 75mm rather than 100mm)	54.0	2.5	-4.4%	3272	1772	5044	5.5%
D8	Assessor errors	An earlier age band assumed by the assessor than reported by the current occupant (wall U-value 1.0 instead of 0.6).	64.8	-4.2	6.9%	5622	1945	7567	-11.7%
D8	Measures installed since EPC issued	Storage heaters replaced by on-peak electric radiators.	40.5	20.2	-33.2%	5302	1944	7246	-15.5%
E6	Measures installed since EPC issued	Storage heaters and hot water cylinder replaced by on-peak electric systems. Low energy lights increased from 0% to 50%	46.7	9.9	-17.5%	5370	1061	6431	-28.0%

Although most of the changes improve the EER some make it worse, which in effect means that some of the changes cancel out in the final new rating.

SAP 10.2

Since all the SERL homes were rated with SAP 2012 all preceding analysis has been undertaken using SAP 2012. SAP10.2 research was considered out of scope of this project. However, as part of the forensic analysis a SAP10.2 calculation was undertaken by the forensic assessor, this is compared with the forensic assessors SAP 2012 calculation, see Figure 88. Note, both the SAP 2012 and SAP10.2 calculations have been undertaken using the details of the property as it was in 2021 (for consistency and to allow comparison with the metered data), not the property as was during the original EPC survey. The below graph shows that almost all homes are rated as having a lower EER using SAP10.2. On average, hot water use is 33.3% higher in gas heated homes, and 1.44% higher for electrically heated homes when using SAP10.2 compared to SAP2012. Meanwhile, space heating energy use is 1.65% lower for gas heated homes, and 0.14% higher for electrically heated homes, when modelled using SAP10.2 compared to SAP2012. On average for gas heated homes, SAP10.2 assessments are 3 EER points less than SAP2012. However, for electrically heated homes the difference can be over 10 EER points despite the small relative change in heating energy use. This is linked to the substantial change in electricity tariffs in SAP10.2. The standard electricity tariff unit rate has increased by 25% while the low rate for the 7-hour electricity tariff increased by 71% (from 5.5 p/KWh to 9.4 p/kWh). Meanwhile the mains gas tariff has increased by only 5%.

[78] Note, electrically heated house E1 had a baseline EPC in 2011 of 73, it has proven difficult to recreate such a high EPC for this flat with its baseline properties and therefore suspect there may have been a software in one of the implementations of SAP used to calculate very historic EPCs.

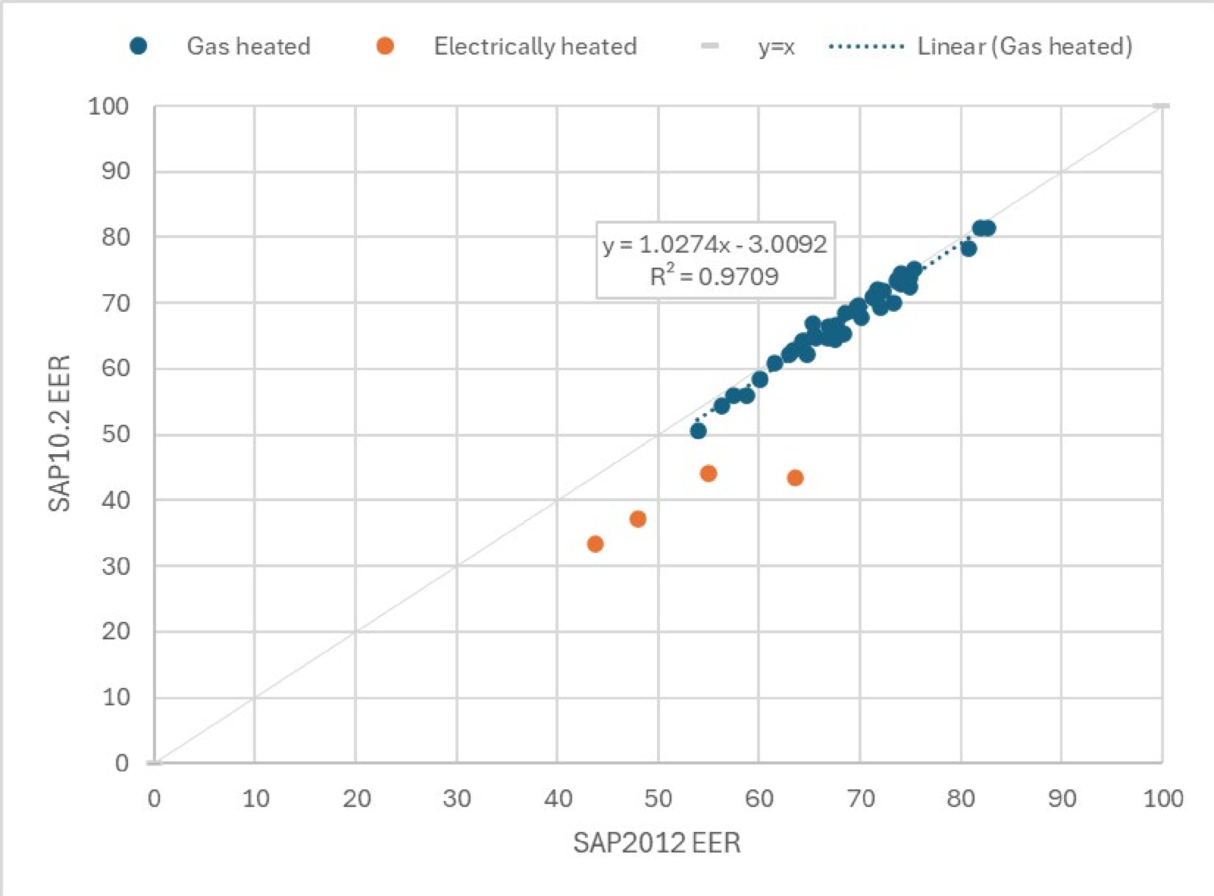

Figure 88 SAP10.2 rating of homes compared to SAP2012 for gas and electrically heated homes

One of the big changes to RdSAP10 is the requirement to measure window areas and record window orientation, whereas RdSAP 2012 assumes default window areas and windows are all oriented East/West. Figure 89 below shows that measuring the window area rather than inferring the window area from the property age-band results in little change on average. This suggests that the measurement of window area will not impact the systematic performance gap observed in this report.

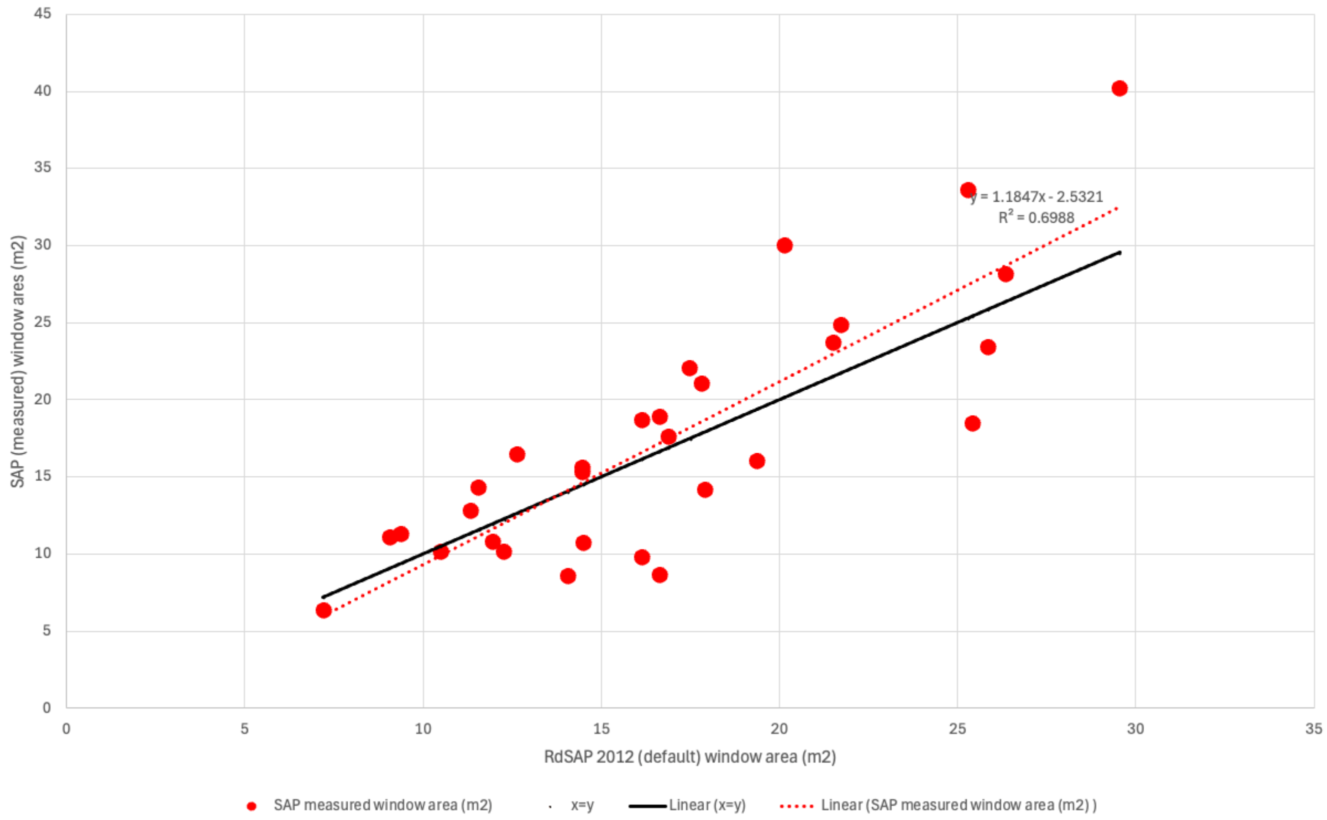

Figure 89 Measured window area versus RdSAP 2012 default window areas for both gas and electrically heated forensic homes.

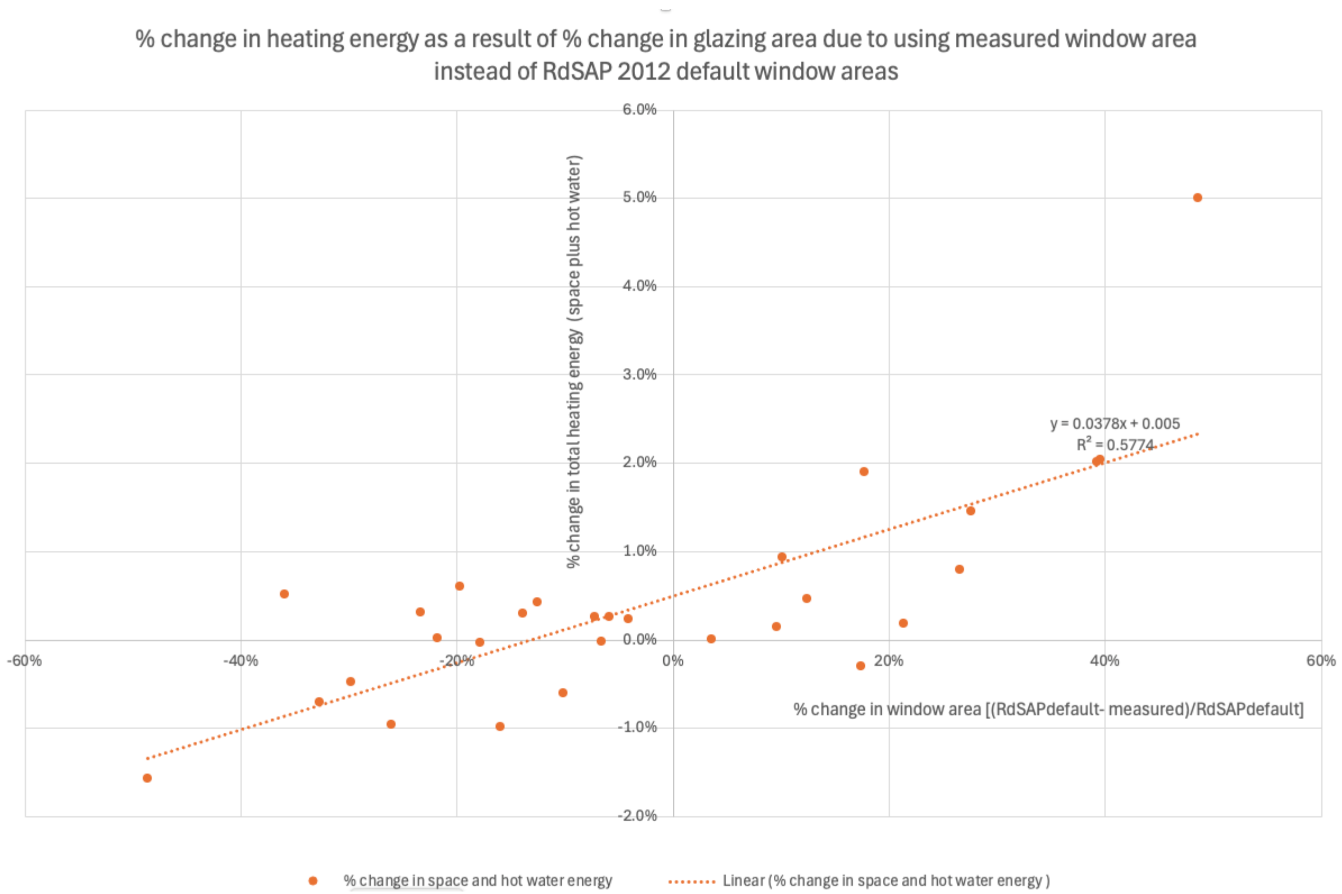

Figure 90 SAP Modelled percentage change in space plus hot water heating energy versus percentage change in window area for Forensic Surveyed homes.

Figure 90 shows how the percentage change in window size impacts the percentage change in total heating energy[79]. On average a 40% change in window area only results in a 2% change in heating energy, there are several causes of this small change. Firstly, the change presented here is for both hot water and space heating. Secondly, in most older existing buildings typical wall U-values are fairly close to U-values for modern secondary glazing (e.g. double glazing is now 1.4 W/K/m2, and in RdSAP solid walls and unfilled cavity walls are assumed to have higher U-values than this until 1976). This means that changing the window to wall ratio has a relatively small impact on the overall U-value for the building envelope as a whole. Finally, although windows lose more heat than walls in modern buildings, they also allow solar gains that can partially offset the increased heat loss.

There is more analysis of the differences between SAP2012 and SAP10.2 modelling in Appendix K which covers the details and findings of the forensic investigations.

[79] RdSAP estimates a total window area and assigns an orientation of East or West. The forensic assessor has measured windows and given them the correct orientation. To generate a model of the original EPC in full SAP 2012 the forensic assessor has subtracted windows so that the total window area matches that which would have been generated for the EPC calculation. When adding a window they have assigned the extra window as East but not changed the orientation of the other windows to East or West

Conclusions – Part 2 Electrically Heated Homes

This part of the report covers traditional electrically heated homes and is complementary to the gas heated part. This analysis compares the monthly energy use for existing electrically heated properties against the EPC modelled energy use in 43 homes, including correcting model predictions for weather, occupancy and regulated interventions post-EPC. In addition, forensic investigations were carried out in 4 homes to identify causes of discrepancies. The SAP modelled mean internal temperature has been compared with measured temperatures in a different sample of 31 buildings. These comparisons provide unique insights into the accuracy of EPCs for traditional electrically heated dwellings. However, it should be noted that compared to gas there are far fewer electrically heated homes in the UK stock, resulting in much smaller sample sizes and challenges to providing statistically significant evidence for this group of homes.

Electrically heated homes have an average performance gap of -31.4%, considerably larger than the average gap of -16.0% for gas heated homes. This gap ranges from -20.7% for energy efficiency rating band C homes to -41.2% for band D homes. By comparison the gap for C-rated gas homes was -6.6% and -34.3% for E-rated homes. In contrast to the gas heated homes, changes to the modelled scenarios made very little difference to the modelled energy use and consequently to the performance gap. There were very few changes modelled as a result of measures recorded in NEED for electrically heated homes, since the majority of measures in NEED are gas boiler replacements which are not relevant. It is nonetheless possible that these homes could have been upgraded since the EPC was carried out, for example window replacement is rarely lodged in NEED but could make a significant difference.

The monthly analysis of the electrically heated homes showed that the discrepancy between metered and modelled energy use was apparent both in the summer and throughout the heating season. The proportional difference was largest during the heating season (to a maximum of -47% in December compared to -20% in July). This suggests that both space heating, and year-round energy use (hot water, appliances, cooking) are likely overestimated for electrically heated properties. Unlike for the gas heated homes, we cannot disaggregate between energy used for water heating in the summer and other summer energy use.

Analysis of the energy signature parameters should be taken as indicative since the sample sizes are small. Nonetheless, it appears that the pattern of HPLP across EPC bands is like that for gas heated homes; C-rated homes show a similar metered HPLP to that which is modelled, while lower bands have a smaller measured HPLP than is modelled. This suggests that homes that are modelled as being the least efficient have better thermal properties than expected. However, the uncertainty is large compared to the difference, and a greater sample size would be required to draw firm conclusions. Moreover, the analysis suggested that there could be a difference in the discrepancy between the metered and modelled HPLP between homes with storage and panel radiators. However, this could be an artefact of the particular samples for each type of heating system and a greater sample size would be needed to explore this issue with greater confidence.

Turning to the temperature analysis from EFUS, SAP models are reasonably closely replicating the MIT in electrically heated properties, with modelled temperatures on average 0.5ºC warmer than measured on average (albeit with a large spread). This is not the case in gas heated homes where SAP assumes a much lower temperature than measured particularly in non-living room area.

Given the small sample sizes we tentatively conclude that EPCs for electric-resistance heated properties have a significant performance gap because they:

- Overpredict year-round electricity use, with the discrepancy being proportionally largest in the winter suggesting heating energy use is particularly poorly modelled.
- Model the mean internal temperature to be warmer than is measured (opposite to gas heated homes), this means that modelling the actual temperature would reduce the performance gap.
- Assume inefficient homes are worse from a space heating efficiency perspective than metered, possibly because homes are ventilated less than SAP assumes, and the fabric is more insulating than SAP assumes, although greater sample sizes would be helpful to draw clearer conclusions.
- Assume solar gains save less space heating fuel than metered, although the effect of this appears to be less than for gas heated homes, possibly because of a greater number of flats and therefore probably more single sided solar gains.

Unlike for the gas heated homes, we did not find that our modelled scenarios improved the performance gap, and we found that the homes re-rated by the expert assessor were often lower rated than their original commercial EPC assessment. This suggests that the issues and potential remedies for electrically heated homes could be quite different than for gas heated homes. Nonetheless, the issues highlighted above suggest some key areas that could be improved in modelling of this group of homes.

In addition to the further work suggested under the gas heated part of the report, specifically for electrically heated homes we recommend that a sample of homes with different electrical heating systems and controls are recruited and monitored. This would firstly enable separation of analysis between homes that have storage heaters compared to panel electric heaters; these systems are operated very differently and so separating them while maintaining appropriate sample sizes would be preferable. Larger sample sizes for both these types of heating systems would allow similar analysis to that performed for the gas sample, including investigating trends among homes of different building characteristics (built form, building age, wall type, etc). Such analysis could help to identify particular groups of homes for which the model performs better and worse.

Appendices

Appendix A: Additional regression analysis

Heating power loss parameter – Model Scenario 0

Table 20 below summarises the goodness of fit parameters for the model of the difference in HPLP.

Table 20 Goodness of fit parameters for the linear model of the difference in HPLP as metered and modelled under scenario 0.

Statistic	Value
Mean absolute error (MAE)	1.26
Root mean square error	2.07
R^2	0.18
Adjusted R^2	0.14

Table 21 below summarises the modelled coefficients and their statistical significance.

Table 21 Modelled coefficients and their statistical significance for the linear model of the difference in HPLP as metered and modelled under scenario 0.

Variable	Coefficient	P-value
Intercept	0.425	0.439
Dwelling age. Reference: pre-1900; treatment: 1900- 1929	0.618	0.190
Dwelling age. Reference: pre-1900; treatment: 1930- 1949	0.527	0.274
Dwelling age. Reference: pre-1900; treatment: 1950- 1966	0.334	0.518
Dwelling age. Reference: pre-1900; treatment: 1967- 1975	0.036	0.947
Dwelling age. Reference: pre-1900; treatment: 1976-1990	0.456	0.412
Dwelling age. Reference: pre-1900; treatment: 1991-2002	0.015	0.981
Dwelling age. Reference: pre-1900; treatment: 2003 onwards	0.679	0.339
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, insulated	-0.611	0.097
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, no insulation	-0.407	0.145
Wall type. Reference: cavity wall, filled cavity; treatment: other	-0.533	0.12
Wall type. Reference: cavity wall, filled cavity; treatment: solid brick, as built, no insulation	**-1.377**	**0.000**
Floor type. Reference: solid, no insulation (assumed); treatment: another dwelling below	**1.145**	**0.002**
Floor type. Reference: solid, no insulation (assumed); treatment: other	-0.758	0.347
Floor type. Reference: solid, no insulation (assumed); treatment: solid, insulated	0.218	0.641
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, insulated	-0.219	0.699
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, no insulation (assumed)	0.092	0.686
Roof type. Reference: pitched, more than 250mm; treatment: another dwelling above	**0.825**	**0.040**
Roof type. Reference: pitched, more than 250mm; treatment: other	-0.026	0.942
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 100 mm loft insulation	0.037	0.908
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 150 mm loft insulation	0.267	0.412
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 200 mm loft insulation	0.103	0.76
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 250 mm loft insulation	0.487	0.152
Roof type. Reference: pitched, more than 250mm; treatment: pitched, less than 100mm loft insulation	-0.501	0.205
Roof type. Reference: pitched, more than 250mm; treatment: pitched, no insulation (assumed)	**-0.889**	**0.016**
Unheated spaces. Reference: all space heated; treatment: has unheated space or no answer	-0.123	0.545
Managing financially. Reference: comfortable; treatment: struggling or no answer	**-0.449**	**0.037**
Hot water system. Reference: combi boiler; treatment: system boiler	0.045	0.822
SAP occupants – survey occupants	**-0.176**	**0.025**
Survey thermostat set point – 21^{o}C	-0.004	0.909
Proportion of total energy use attributed to secondary heating	**-6.430**	**0.000**

Baseline Energy Use Intensity – Model Scenario 0

Table 22 below summarises the goodness of fit indicators of the regression model for the difference in baseline EUI, and Table 23 summarises the coefficients and their statistical significance.

Table 22 Goodness of fit parameters for the linear model of the difference in baseline EUI as metered and modelled under scenario 0.

Statistic	Value
Mean absolute error	0.063
Root mean square error	0.084
R^2	0.22
Adjusted R^2	0.18

Table 23 Modelled coefficients and their statistical significance for the linear model of the difference in baseline EUI as metered and modelled under scenario 0.

Variable	Coefficient	P-value
Intercept	-0.014	0.53
Dwelling age. Reference: pre-1900; treatment: 1900- 1929	**0.048**	**0.01**
Dwelling age. Reference: pre-1900; treatment: 1930- 1949	**0.046**	**0.02**
Dwelling age. Reference: pre-1900; treatment: 1950- 1966	0.030	0.15
Dwelling age. Reference: pre-1900; treatment: 1967- 1975	0.011	0.61
Dwelling age. Reference: pre-1900; treatment: 1976-1990	0.037	0.10
Dwelling age. Reference: pre-1900; treatment: 1991-2002	0.030	0.24
Dwelling age. Reference: pre-1900; treatment: 2003 onwards	0.037	0.20
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, insulated	-0.003	0.83
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, no insulation	**0.026**	**0.02**
Wall type. Reference: cavity wall, filled cavity; treatment: other	-0.001	0.97
Wall type. Reference: cavity wall, filled cavity; treatment: solid brick, as built, no insulation	-0.001	0.97
Floor type. Reference: solid, no insulation (assumed); treatment: another dwelling below	-0.014	0.35
Floor type. Reference: solid, no insulation (assumed); treatment: other	0.012	0.72
Floor type. Reference: solid, no insulation (assumed); treatment: solid, insulated	0.015	0.43
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, insulated	-0.018	0.42
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, no insulation (assumed)	-0.002	0.82
Roof type. Reference: pitched, more than 250mm; treatment: another dwelling above	-0.026	0.12
Roof type. Reference: pitched, more than 250mm; treatment: other	0.024	0.09
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 100 mm loft insulation	-0.006	0.67
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 150 mm loft insulation	-0.003	0.82
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 200 mm loft insulation	0.016	0.24
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 250 mm loft insulation	**0.027**	**0.05**
Roof type. Reference: pitched, more than 250mm; treatment: pitched, less than 100mm loft insulation	0.006	0.72
Roof type. Reference: pitched, more than 250mm; treatment: pitched, no insulation (assumed)	0.010	0.51
Unheated spaces. Reference: all space heated; treatment: has unheated space or no answer	0.003	0.70
Managing financially. Reference: comfortable; treatment: struggling or no answer	**-0.017**	**0.05**
Hot water system. Reference: combi boiler; treatment: system boiler	**-0.030**	**0.00**
SAP occupants – survey occupants	**-0.029**	**0.00**
Survey thermostat set point – 21°C	**0.005**	**0.00**
Proportion of total energy use attributed to secondary heating	0.030	0.60

Energy performance gap – Model Scenario 4

Table 24 shows the goodness of fit parameters for the model of the difference between metered annual EUI and modelled EUI under scenario 4. The overall summary performance is quite similar to that found using scenario 0. Table 25 shows the coefficients and their significance. Interestingly, only three coefficients are significant in this model. Compared to the results for model 0, we see that none of the wall types are now significant, suggesting that the updates to U-values carried out in the most recent versions of RdSAP have improved the modelling of this parameter. None of the building ages are significant, although as noted for scenario 0, the building age influences several other parameters non-directly and the structure of this model does not take this into account. Two roof types are significant in the current results, the group which are recorded as having no insulation and the group with another dwelling above. This suggests that it is likely that many homes which are recorded as having no loft insulation do actually have loft insulation, and that homes with another dwelling above perform better than expected. The proportion of secondary heating remains significant, although it is worth noting that the proportion is always less than 10%, so the effect is at maximum similar to that for homes with another dwelling above.

Table 24 Goodness of fit parameters for the linear model of the difference in annual EUI as metered and modelled under scenario 4.

Statistic	Value
Mean absolute error	41.4
Root mean square error	54.4
R^2	0.17
Adjusted R^2	0.13

Table 25 Modelled coefficients and their statistical significance for the linear model of the difference in annual EUI as metered and modelled under scenario 4.

Variable	Coefficient	P-value
Intercept	-16.9	0.187
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, insulated	6.2	0.478
Wall type. Reference: cavity wall, filled cavity; treatment: cavity wall, as built, no insulation	-6.3	0.383
Wall type. Reference: cavity wall, filled cavity; treatment: other	-8.4	0.296
Wall type. Reference: cavity wall, filled cavity; treatment: solid brick, as built, no insulation	-10.4	0.203
Floor type. Reference: solid, no insulation (assumed); treatment: another dwelling below	2.3	0.783
Floor type. Reference: solid, no insulation (assumed); treatment: other	-10.4	0.619
Floor type. Reference: solid, no insulation (assumed); treatment: solid, insulated	6.8	0.556
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, insulated	3.5	0.808
Floor type. Reference: solid, no insulation (assumed); treatment: suspended, no insulation (assumed)	1.5	0.782
Dwelling age. Reference: pre-1900; treatment: 1900 - 1929	-0.5	0.968
Dwelling age. Reference: pre-1900; treatment: 1930 - 1949	16.9	0.144
Dwelling age. Reference: pre-1900; treatment: 1950 - 1966	5.4	0.659
Dwelling age. Reference: pre-1900; treatment: 1967 - 1975	-3.2	0.805
Dwelling age. Reference: pre-1900; treatment: 1976-1990	17.2	0.192
Dwelling age. Reference: pre-1900; treatment: 1991-2002	3.7	0.808
Dwelling age. Reference: pre-1900; treatment: 2003 onwards	16.1	0.353
Roof type. Reference: pitched, more than 250mm; treatment: another dwelling above	**-20.7**	**0.025**
Roof type. Reference: pitched, more than 250mm; treatment: other	-1.4	0.872
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 100 mm loft insulation	-8.8	0.253
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 150 mm loft insulation	-1.4	0.861
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 200 mm loft insulation	14.0	0.068
Roof type. Reference: pitched, more than 250mm; treatment: pitched, 250 mm loft insulation	10.8	0.174
Roof type. Reference: pitched, more than 250mm; treatment: pitched, less than 100mm loft insulation	-14.5	0.160
Roof type. Reference: pitched, more than 250mm; treatment: pitched, no insulation (assumed)	**-42.9**	**0.000**
Unheated spaces. Reference: all space heated; treatment: has unheated space or no answer	-6.4	0.187
Managing financially. Reference: comfortable; treatment: struggling or no answer	-6.9	0.170
Hot water system. Reference: combi boiler; treatment: system boiler	-8.6	0.148
Proportion of total energy use attributed to secondary heating	**-194.6**	**0.000**

Appendix B: EPC registry analysis

The following figures replicate the analysis of the EPC registry database in the main report but here only include EPCs generated since the introduction of SAP2012. This is a smaller subset of homes because relatively few have both a new home EPC and a subsequent EPC generated since 2012. The overall trends are very similar to the whole sample.

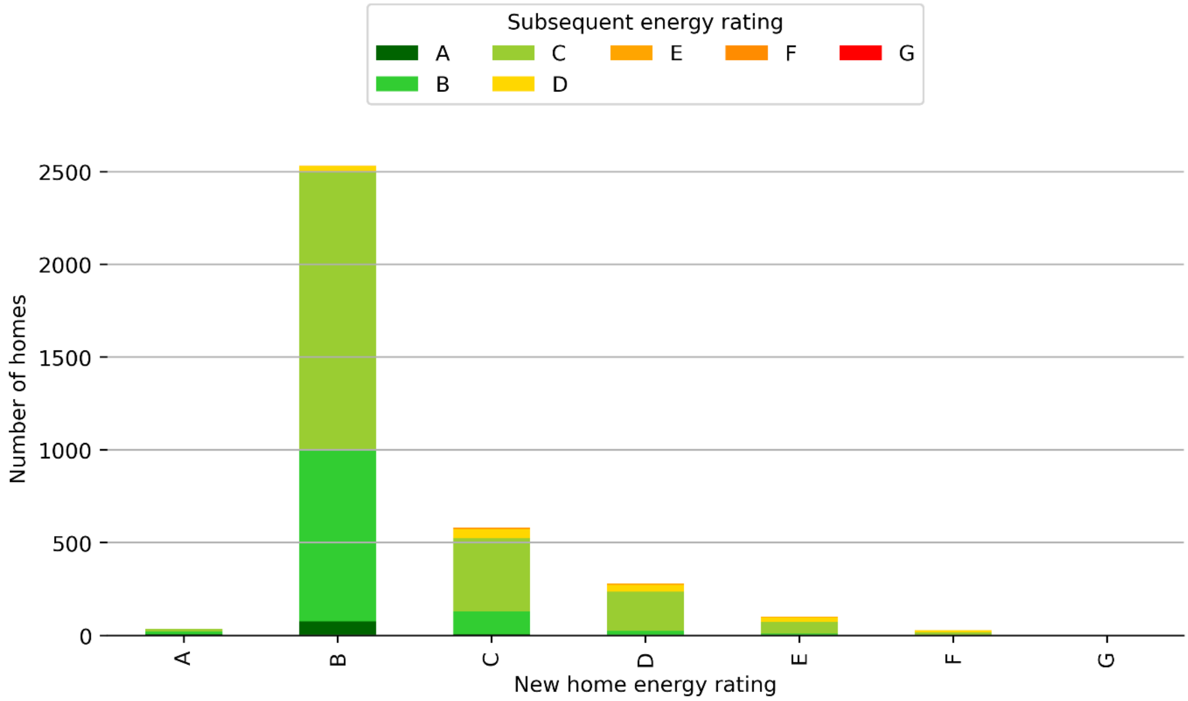

Figure 91 Bar chart of EPC ratings for homes with a new home rating and a subsequent marketed sale ratings, both generated since the introduction of SAP2012. The height of the bars shows the number of homes in each rating when first rated, and the stacked bars show the number of these subsequently in each band when the EPC is regenerated via another RdSAP

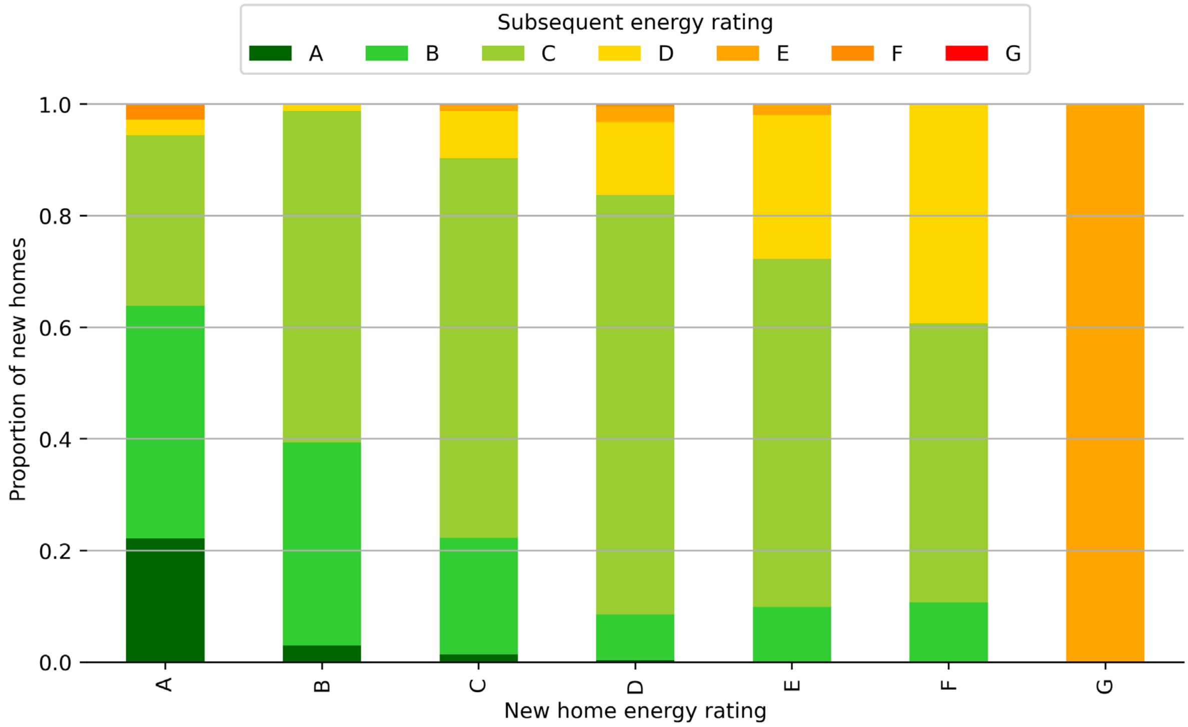

Figure 92 Bar chart of EPC ratings for homes with new ratings and subsequent marketed sale ratings. The x-axis reflects the EPC band when rated as new, and the height of the stacked bars shows the proportion of these subsequently rated into each band when the EPC is generated for a marked sale under RdSAP

Appendix C: Typical building characteristics of gas heated properties in different EPC bands

Table 26 was created by analysing the outputs produced from NBM populated with the English Housing Stock data for just gas heated homes. Where monthly variables are summarised only the winter period is included. This provides some guidance as to the sample characteristics.

Table 26 Average building characteristics of homes in different EPC bands. Sample sizes for each band are as follows: A&B – 185, C – 4101, D – 4975, E – 996, F&G 99.

SAP_letter_score	Variable	25%	50%	75%	mean	std
A&B	201 Secondary heating fraction	0	0	0	0.02	0.04
A&B	206 Main heating1 efficiency (%)	89.5	89.8	90	88.73	3.15
A&B	211 Annual main space heat1 fuel (kWh / year)	2088.51	4415.55	7033.78	5301.96	4051.47
A&B	211m Monthly main space heat1 fuel (kWh / month)					
A&B	215 Annual secondary space heat fuel (kWh / year)	0	0	0	253.64	785.72
A&B	215m Monthly secondary space heat fuel (kWh / month)					
A&B	216 Efficiency of water heater (%)	79.1	79.6	86.7	81.11	5.2
A&B	219 Annual water heater fuel (kWh / year)	2182.83	2433.55	2791.91	2529.86	545.02
A&B	22b_nbm_infiltration_rate	0.47	0.54	0.61	0.55	0.11
A&B	231 Annual kwh pumps fans etc (kWh / year)	75	165	165	141.58	44.29
A&B	232 Annual kwh lighting (kWh / year)	353.52	494.83	662.96	533.52	237.06
A&B	35_TMP	250	250	250	249.73	73.08
A&B	37_total_fabric_heat_loss	46.09	87.08	145.12	106.02	73.95
A&B	39_Monthly_HTC	76.37	125.31	190.47	153.29	97.73
A&B	40_Average_HLP	1.19	1.53	2.09	1.68	0.61
A&B	44_hot_water	1021.04	1151.43	1259.24	1135.77	139.13
A&B	73m Monthly internal heat gains (W / month)	446.79	556.24	675.24	578.9	165.28
A&B	84 Total of monthly total gains - internal and solar (	7762.11	10169.88	14136.46	12007.1	6131.53
A&B	84mMonthlyGains	623.07	819.56	1094.29	940.42	491.39
A&B	85 Living area target temp (Celsius)	21	21	21	21	0
A&B	87_nbm_living_area_temp	19.49	20.1	20.5	19.95	0.7
A&B	88 Total of monthly rest of dwelling target temp (Cel	231.69	235.94	239.23	235.12	4.91
A&B	90m_nbm_rest_of_dwelling_temp	18.06	18.84	19.43	18.69	0.92
A&B	91 Living area fraction	0.21	0.25	0.3	0.28	0.11
A&B	93m_nbm_whole_dwelling	18.38	19.16	19.73	19.02	0.91
A&B	95m Monthly useful gains (W / month)	557.16	723.08	961.92	833.13	410.88
A&B	96_nbm_external_temp	5.1	7.4	9.95	7.97	2.8
A&B	98 Annual space heating requirement (kWh / year)	1877.57	3984.62	6302.27	4843.95	3845.12
A&B	98m Monthly space heating requirement (kWh / mo	207.93	410.61	796.98	605.49	594.3
A&B	Dwelling_Volume	140.3	190.57	249.6	219.85	122.34
A&B	Energy_content_hot_water	1338.75	1509.7	1651.06	1489.17	182.42
A&B	Infilration_rate_incorporating_shelter	0.48	0.53	0.6	0.55	0.09
A&B	MonthlyHLP	1.2	1.56	2.11	1.7	0.61
A&B	MonthlyLivingAreaUtilFactor	0.9	0.96	0.98	0.93	0.08
A&B	MonthlyRestofDwellingUtilFactor	0.86	0.95	0.98	0.9	0.11
A&B	SAP_rating	81	82	84	83.22	3.22
A&B	Total_floor_area	59.36	76.74	102.02	90.14	48.61
A&B	nbm_ach_effective_25	0.61	0.64	0.69	0.66	0.06

C	201 Secondary heating fraction	0	0	0.1	0.03	0.05
C	206 Main heating1 efficiency (%)	85.4	89.7	90	87.58	4.39
C	211 Annual main space heat1 fuel (kWh / year)	5013.81	6845.1	9017.55	7500.45	3837
C	211m Monthly main space heat1 fuel (kWh / month)					
C	215 Annual secondary space heat fuel (kWh / year)	0	0	552.13	447.8	976.11
C	215m Monthly secondary space heat fuel (kWh / month)					
C	216 Efficiency of water heater (%)	78.9	79.6	83.5	79.98	6.36
C	219 Annual water heater fuel (kWh / year)	2228.12	2498.9	2938.53	2646.19	642.68
C	22b_nbm_infiltration_rate	0.5	0.58	0.68	0.6	0.13
C	231 Annual kwh pumps fans etc (kWh / year)	165	165	165	165.16	24.34
C	232 Annual kwh lighting (kWh / year)	395.3	512.71	652.18	538.4	207.42
C	35_TMP	250	250	250	269.18	78.05
C	37_total_fabric_heat_loss	97.07	133.24	179.62	148.09	76.45
C	39_Monthly_HTC	129.05	175.12	229.26	193.04	96.65
C	40_Average_HLP	2	2.4	2.74	2.38	0.51
C	44_hot_water	1007.21	1134.02	1221.55	1115.66	138.58
C	73m Monthly internal heat gains (W / month)	455.21	552.4	650.06	565.32	150.88
C	84 Total of monthly total gains - internal and solar (	8113.15	10852.47	14040.26	11921.55	5602.61
C	84mMonthlyGains	638.66	825.85	1082.76	930.26	456.62
C	85 Living area target temp (Celsius)	21	21	21	21	0
C	87_nbm_living_area_temp	18.95	19.51	20.02	19.47	0.71
C	88 Total of monthly rest of dwelling target temp (Cel	226.81	229.41	232.99	230.03	4.35
C	90m_nbm_rest_of_dwelling_temp	17.33	17.96	18.51	17.91	0.83
C	91 Living area fraction	0.21	0.25	0.3	0.28	0.11
C	93m_nbm_whole_dwelling	17.75	18.38	18.93	18.33	0.82
C	95m Monthly useful gains (W / month)	595.95	767.53	982.62	840.02	364.02
C	96_nbm_external_temp	5.1	7.4	9.95	7.79	2.78
C	98 Annual space heating requirement (kWh / year)	4508.3	6169.41	8183.8	6832.71	3616.17
C	98m Monthly space heating requirement (kWh / mo	440.41	725.94	1113.6	854.09	600.8
C	Dwelling_Volume	139.58	183.77	228.1	201.17	97.16
C	Energy_content_hot_water	1320.61	1486.89	1601.64	1462.81	181.7
C	Infilration_rate_incorporating_shelter	0.5	0.57	0.65	0.58	0.11
C	MonthlyHLP	2.01	2.41	2.76	2.4	0.52
C	MonthlyLivingAreaUtilFactor	0.93	0.97	0.99	0.95	0.06
C	MonthlyRestofDwellingUtilFactor	0.9	0.96	0.98	0.93	0.08
C	SAP_rating	70	72	75	72.87	3.12
C	Total_floor_area	57.75	74.04	90.45	81.19	37.87
C	nbm_ach_effective_25	0.63	0.67	0.73	0.69	0.09
D	201 Secondary heating fraction	0	0.1	0.1	0.07	0.05

D	201 Secondary heating fraction	0	0.1	0.1	0.07	0.05
D	206 Main heating1 efficiency (%)	79.8	89.1	89.8	84.16	7.75
D	211 Annual main space heat1 fuel (kWh / year)	8615.02	10970.87	14112.44	12266.04	5871.65
D	211m Monthly main space heat1 fuel (kWh / month)					
D	215 Annual secondary space heat fuel (kWh / year)	0	916.02	2083.01	1479.04	1821.72
D	215m Monthly secondary space heat fuel (kWh / month)					
D	216 Efficiency of water heater (%)	70.9	79.3	79.8	76.64	9.31
D	219 Annual water heater fuel (kWh / year)	2355.22	2589.85	3224.29	2953.5	1041.99
D	22b_nbm_infiltration_rate	0.58	0.68	0.81	0.71	0.18
D	231 Annual kwh pumps fans etc (kWh / year)	165	165	165	168.37	26.66
D	232 Annual kwh lighting (kWh / year)	451.08	568.08	700.17	586.74	202.13
D	35_TMP	250	250	450	305.95	92.95
D	37_total_fabric_heat_loss	165.19	211.86	275.52	236.81	113.78
D	39_Monthly_HTC	207.29	261.5	334.3	290.89	136.82
D	40_Average_HLP	2.91	3.26	3.78	3.38	0.65
D	44_hot_water	1066.08	1167.76	1248.7	1145.85	129.44
D	73m Monthly internal heat gains (W / month)	495.47	584.69	685.27	600.46	154.5
D	84 Total of monthly total gains - internal and solar (	9817.57	12714.16	16304.56	13807.16	6017.56
D	84mMonthlyGains	739.36	946.64	1248.65	1064.45	507.35
D	85 Living area target temp (Celsius)	21	21	21	21	0
D	87_nbm_living_area_temp	18.41	18.99	19.61	18.99	0.78
D	88 Total of monthly rest of dwelling target temp (Cel	221.4	224.13	226.86	224.72	4.76
D	90m_nbm_rest_of_dwelling_temp	16.53	17.15	17.78	17.14	0.87
D	91 Living area fraction	0.21	0.21	0.25	0.25	0.09
D	93m_nbm_whole_dwelling	16.99	17.62	18.25	17.61	0.87
D	95m Monthly useful gains (W / month)	705.92	890.61	1136.11	970.61	404.58
D	96_nbm_external_temp	5.1	7.1	9.95	7.64	2.76
D	98 Annual space heating requirement (kWh / year)	7817.71	9877.1	12759.83	11079.35	5412.11
D	98m Monthly space heating requirement (kWh / mo	786.36	1213.77	1743.31	1384.92	887.6
D	Dwelling_Volume	163.02	201.91	251.69	219.67	98.41
D	Energy_content_hot_water	1397.8	1531.12	1637.24	1502.39	169.71
D	Infilration_rate_incorporating_shelter	0.55	0.66	0.76	0.67	0.16
D	MonthlyHLP	2.93	3.29	3.8	3.4	0.65
D	MonthlyLivingAreaUtilFactor	0.95	0.98	0.99	0.96	0.05
D	MonthlyRestofDwellingUtilFactor	0.92	0.97	0.98	0.94	0.07
D	SAP_rating	60	64	66	63.2	3.73
D	Total_floor_area	64.8	79.46	98.21	86.49	37.21
D	nbm_ach_effective_25	0.67	0.73	0.83	0.76	0.14

E	201 Secondary heating fraction	0.1	0.1	0.1	0.08	0.04
E	206 Main heating1 efficiency (%)	69	81.5	89.7	78.68	10.63
E	211 Annual main space heat1 fuel (kWh / year)	15915.66	20530.36	26235.79	23093.49	13746
E	211m Monthly main space heat1 fuel (kWh / month)					
E	215 Annual secondary space heat fuel (kWh / year)	1307.14	2833.82	5637.09	3991.66	4303.53
E	215m Monthly secondary space heat fuel (kWh / month)					
E	216 Efficiency of water heater (%)	62	74.85	79.7	71.62	12.4
E	219 Annual water heater fuel (kWh / year)	2562.69	2934.09	4291.8	3723.75	1789.74
E	22b_nbm_infiltration_rate	0.71	0.84	0.98	0.85	0.2
E	231 Annual kwh pumps fans etc (kWh / year)	165	165	165	164.43	30.24
E	232 Annual kwh lighting (kWh / year)	539.28	673.11	827.82	702.63	247
E	35_TMP	250	450	450	367.52	101.88
E	37_total_fabric_heat_loss	277.91	366.93	488.59	415.2	238.26
E	39_Monthly_HTC	331.36	431.99	577.64	496.36	293.66
E	40_Average_HLP	3.99	4.53	5.11	4.59	0.92
E	44_hot_water	1146.09	1240.73	1294.54	1206.44	121.1
E	73m Monthly internal heat gains (W / month)	578.41	683.86	806.45	701.56	185.88
E	84 Total of monthly total gains - internal and solar (	11647.1	15116.18	19741.59	16733.66	8944.57
E	84mMonthlyGains	875.22	1120.8	1492.42	1285.05	733.07
E	85 Living area target temp (Celsius)	21	21	21	21	0
E	87_nbm_living_area_temp	18.09	18.66	19.32	18.65	0.86
E	88 Total of monthly rest of dwelling target temp (Cel	217.04	218.76	223.21	220.75	5.2
E	90m_nbm_rest_of_dwelling_temp	15.92	16.58	17.27	16.58	0.96
E	91 Living area fraction	0.18	0.21	0.25	0.22	0.07
E	93m_nbm_whole_dwelling	16.4	17.06	17.77	17.07	0.99
E	95m Monthly useful gains (W / month)	845.08	1070.13	1396.82	1199.31	636
E	96_nbm_external_temp	5.1	7.1	9.95	7.63	2.76
E	98 Annual space heating requirement (kWh / year)	13280.36	17488.11	23189.15	19983.01	12271.59
E	98m Monthly space heating requirement (kWh / mo	1401.39	2130.27	3100.88	2497.88	1839.33
E	Dwelling_Volume	192.55	249.07	323.76	286.06	179.1
E	Energy_content_hot_water	1502.71	1626.8	1697.34	1581.84	158.78
E	Infilration_rate_incorporating_shelter	0.69	0.8	0.92	0.81	0.18
E	MonthlyHLP	4.02	4.57	5.14	4.62	0.92
E	MonthlyLivingAreaUtilFactor	0.97	0.99	0.99	0.97	0.04
E	MonthlyRestofDwellingUtilFactor	0.94	0.98	0.99	0.95	0.06
E	SAP_rating	46	50	53	49.03	4.19
E	Total_floor_area	75.89	95.68	123.27	109.5	64.46
E	nbm_ach_effective_25	0.75	0.85	0.98	0.88	0.17

F&G	201 Secondary heating fraction	0.1	0.1	0.1	0.08	0.04
F&G	206 Main heating1 efficiency (%)	61	64	74.2	66.62	12.91
F&G	211 Annual main space heat1 fuel (kWh / year)	23566.98	31565.46	44211.23	37065.05	19681.04
F&G	211m Monthly main space heat1 fuel (kWh / month)					
F&G	215 Annual secondary space heat fuel (kWh / year)	2006.4	5150.69	9560.04	6470.48	5943.57
F&G	215m Monthly secondary space heat fuel (kWh / month)					
F&G	216 Efficiency of water heater (%)	51	62	75	65.25	16.3
F&G	219 Annual water heater fuel (kWh / year)	2944.32	4370.37	6850.44	4994.26	2511.81
F&G	22b_nbm_infiltration_rate	0.85	1.01	1.15	1.01	0.25
F&G	231 Annual kwh pumps fans etc (kWh / year)	120	156	165	142.49	63.62
F&G	232 Annual kwh lighting (kWh / year)	583.71	739.96	942.75	778.95	282.27
F&G	35_TMP	250	450	450	385.35	104.33
F&G	37_total_fabric_heat_loss	333.23	474.17	681.23	538.24	271.51
F&G	39_Monthly_HTC	389.63	566.57	818.12	644.62	336.03
F&G	40_Average_HLP	4.64	5.22	5.87	5.41	1.08
F&G	44_hot_water	1162.31	1260	1312.57	1223.38	122.76
F&G	73m Monthly internal heat gains (W / month)	633.34	786.25	962.55	795.78	215.88
F&G	84 Total of monthly total gains - internal and solar (	12773.01	16761.39	24263.35	18927.42	9120.12
F&G	84mMonthlyGains	963.88	1274.96	1710.41	1449.94	766.1
F&G	85 Living area target temp (Celsius)	21	21	21	21	0
F&G	87_nbm_living_area_temp	17.88	18.44	19.13	18.41	0.93
F&G	88 Total of monthly rest of dwelling target temp (Cel	216.32	217.8	222.22	218.97	4.85
F&G	90m_nbm_rest_of_dwelling_temp	15.69	16.33	17	16.29	0.97
F&G	91 Living area fraction	0.16	0.18	0.21	0.2	0.07
F&G	93m_nbm_whole_dwelling	16.16	16.92	17.56	16.88	0.99
F&G	95m Monthly useful gains (W / month)	925.23	1232.58	1595.19	1364.71	679.81
F&G	96_nbm_external_temp	5.1	7.1	9.95	7.6	2.74
F&G	98 Annual space heating requirement (kWh / year)	16504.71	23133.55	33593.21	26705.13	14653.11
F&G	98m Monthly space heating requirement (kWh / mo	1869.35	2780.27	4252.57	3338.14	2224.64
F&G	Dwelling_Volume	198.27	277.33	388.32	330.22	218.38
F&G	Energy_content_hot_water	1523.98	1652.05	1720.98	1604.04	160.96
F&G	Infilration_rate_incorporating_shelter	0.79	0.95	1.09	0.94	0.22
F&G	MonthlyHLP	4.68	5.26	5.92	5.45	1.08
F&G	MonthlyLivingAreaUtilFactor	0.97	0.99	1	0.98	0.03
F&G	MonthlyRestofDwellingUtilFactor	0.95	0.98	0.99	0.96	0.05
F&G	SAP_rating	30	35	37	32.49	6.36
F&G	Total_floor_area	78.53	102.32	150.67	122.53	70.75
F&G	nbm_ach_effective_25	0.86	1.01	1.15	1.02	0.23

Appendix E: Validation of conversion of EPC input data to NBM model outputs

Connecting EPC input data as provided by DESNZ to NBM modelling is a non-trivial task which has involved a major effort as part of this project. Figure 93 is a schematic of the process which involves the following:

- tidy the raw EPC input data…
- reformat data for NBM using a mix of RdSAP documentation, and the XSD files,
- different steps are then used to replicate different versions of RdSAP where appropriate,

The available EPC data does not include the breakdown of the SAP working calculations and final outputs. Comparison is therefore done between the NBM calculations and the real EPCs using the SAP score (ratings model) and gas/electricity use figures reverse-engineered from the available performance outputs

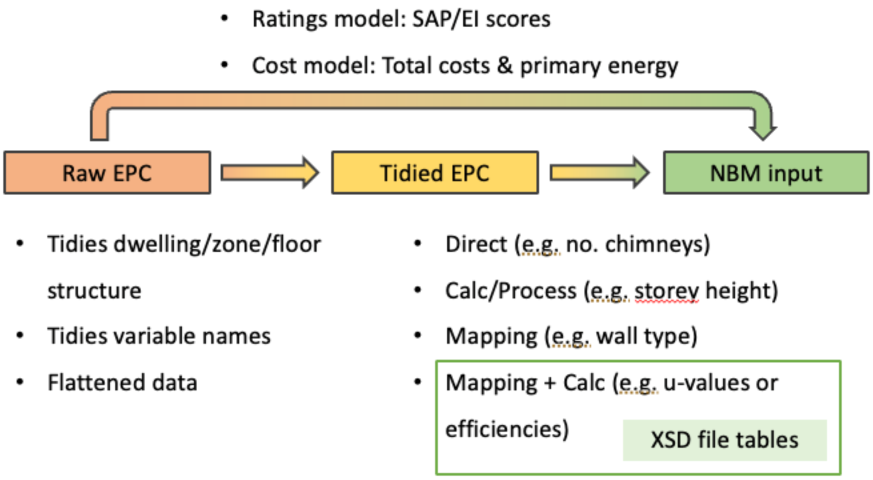

Figure 93 Schematic of EPC input data processing to produce an NBM input file

Figure 94 shows the comparison between the NBM calculated SAP and the EPC assessor SAP in the EPC Registry. NBM SAP scores are within +/- 1 point from the EPC scores for 91% of EPCs, and within +/-2 points for 96%, (note that SAP score is only presented as an integer in the Registry data). The charts show that NBM matches well with EPCs across each RdSAP type in the dataset. We chose to apply a requirement that the NBM SAP score be within 2 of the EPC SAP score.

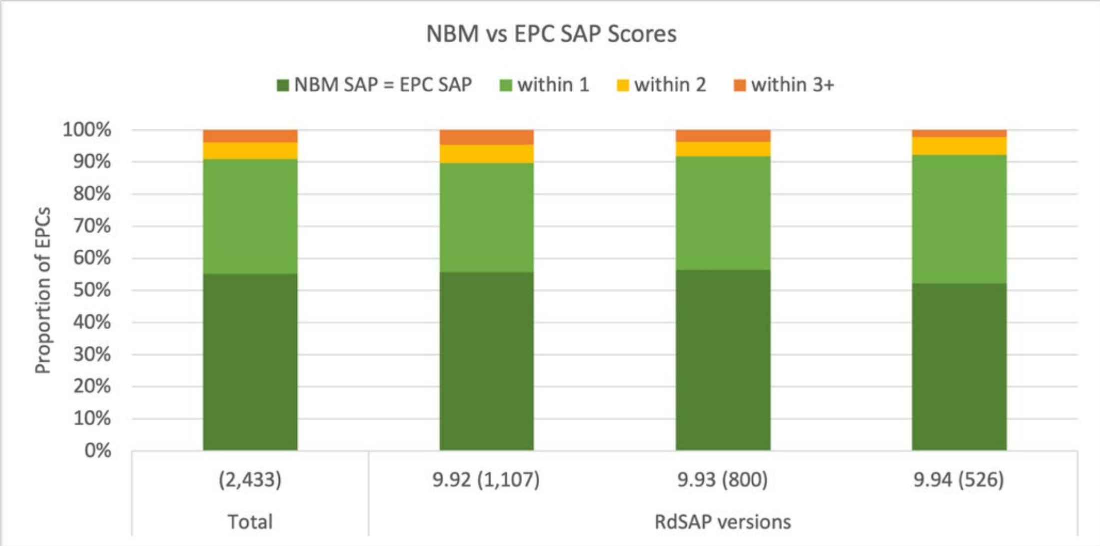

Figure 94 Comparison between the NBM calculated SAP and the EPC assessor SAP in the EPC Registry for different versions of RdSAP, different colours of bars denote the difference in SAP points between the two methods of calculating the SAP.

Figure 95 shows the impact of different version of RdSAP on the SAP score for each EPC band. Each EPC originally run under RdSAP 9.92 has been re-run under RdSAP 9.94, (the main changes in assumptions between these RdSAP versions are the default assumptions about wall & floor elements). While the SAP score remains unchanged for 39% of homes, most homes would see a slight shift in their score, up/down depending on the existing construction (and thus linked to the EPC score).

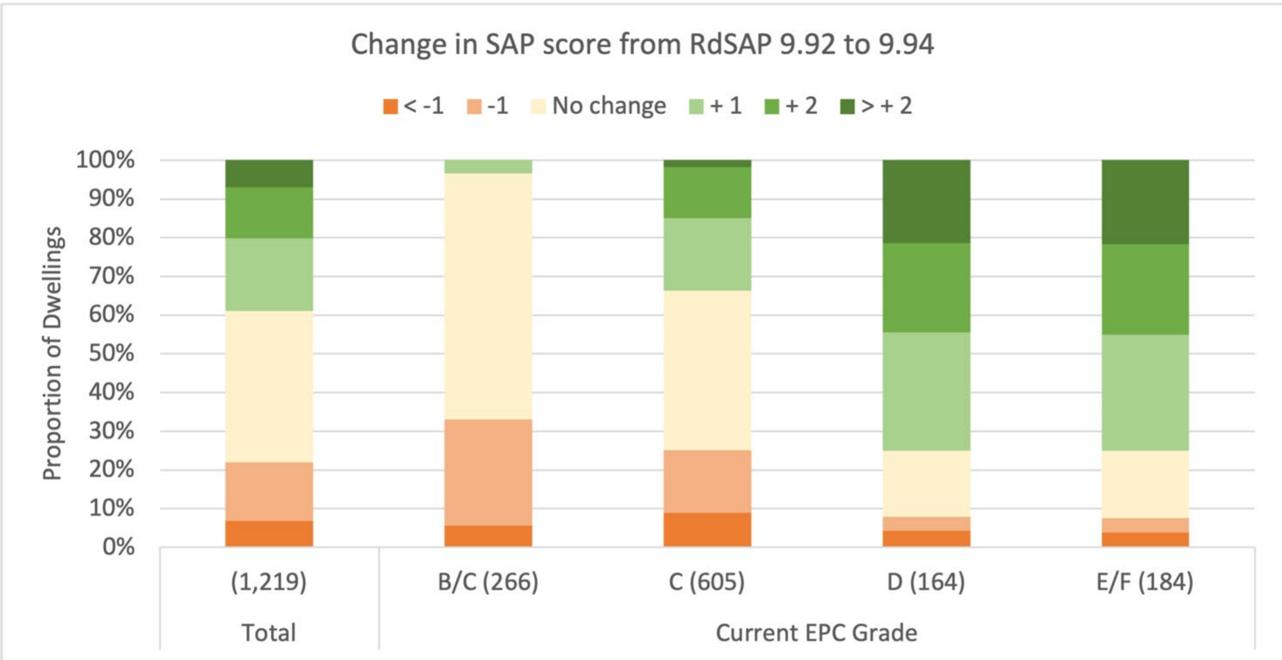

Figure 95 The impact of different version of RdSAP on the SAP score for each EPC band

Appendix F: Validation of MIT analysis: comparison with GHG

Temperature data was collected in 200 dwellings as part of the DESNZ's evaluation of the Green Homes Grant (GHG), where temperature loggers were installed in 4 rooms (including the living room, kitchen, hallway, and main bedroom) in each house after the GHG measure was installed, and smart meter data was also collected during this period. The sample was collected during the winters of 2021-2022 and 2022-2023. The same homes are not represented in each winter, with the 2021 homes being Local Authority, and the 2023 homes being largely owner occupied and in receipt of vouchers to finance energy efficiency upgrades. Further details of this data is available in the reporting for the GHG-SMETER project (GHG-SMETER).

Temperature Data cleaning: For the GHG-SMETER data, the cleaning process was done manually within the GHG-SMETER project. This meant examining each temperature time series to find the start and end point (i.e., when it appeared that the temperature sensor had been placed in the correct room and was not in transit, and the most likely end point for the analysis), and to identify issues with sensor placement or sensor failure. Brief notes on the heating patterns were also recorded, and any data where it was clear that solar radiation was incident on the sensor was excluded entirely. No further cleaning was required after this process was completed. The time series temperature data was then aggregated to form monthly Mean Internal Temperatures for the available rooms, as well as an overall mean temperature (the monthly mean of room means), and a Zone 2 temperature (the mean of all rooms minus the living room).

Hourly external temperature data was provided by the SERL Observatory[80] (via the Copernicus/ECMWF ERA5 hourly reanalysis dataset[81]), and matched to the internal temperatures for the closest grid cell. Each grid cell is approximately 28km^2, and hourly temperatures were down-sampled to monthly means in order to provide the best comparison to the SAP/NBM-SERL.

Figure 96 compares GHG with the EFUS data, note the modelled data refers to the NBM predicted modelled internal temperature for the EFUS sample, there is no directly equivalent modelled data for the GHG temperature data.

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[80] Elam, S., Webborn, E., McKenna, E., Oreszczyn, T., Anderson, B., Ministry of Housing, Communities and Local Government, European Centre for Medium-Range Weather Forecasts, Royal Mail Group Limited. (2021). Smart Energy Research Lab Observatory Data, 2019-2020: Secure Access. [data collection]. 3rd Edition. UK Data Service. SN: 8666, DOI: http://doi.org/10.5255/UKDA-SN-8666-3

[81] ECMWF. ERA5 ECMWF. Available online: https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

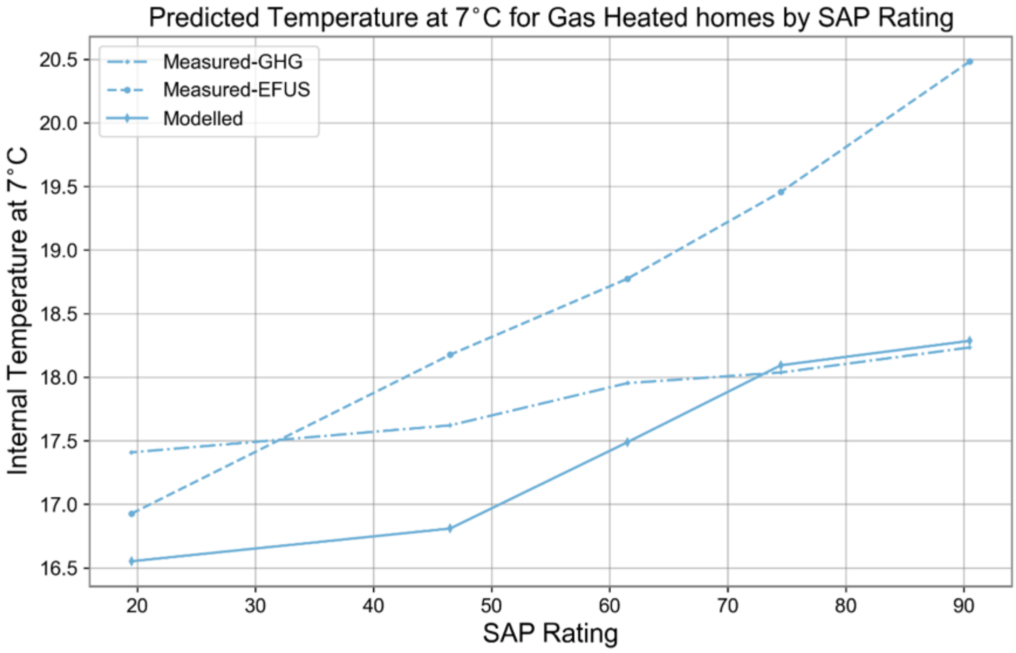

Figure 96 Mean internal temperature variation with SAP score for different data sets (GHG and EFUS, compared against the EFUS modelled

Appendix G: NEED annual data analysis – testing the validity of the SERL analysis

Although SERL data is extremely useful because of the combination of smart meter data with contextual data, it is only available for a maximum of 13,000 properties, with the number available falling significantly when multiple constraints are applied to the data. This means that the sample is small for particular combinations of building characteristics, and it can be challenging to attribute issues to buildings with particular characteristics. On the other hand, NEED has data for each property with metered energy consumption (electricity and gas), and so has much larger sample sizes, but less occupant contextual data and no monthly energy data to compare with SAP model predictions.

NEED data has been compared against SAP model predictions for 300,000 homes in London as part of a paper in preparation by Daniel Godoy[82]. Below are, examples of data analysis undertaken which indicate (see Figure 97 and Figure 98) NEED data and SERL data consistently predict a performance gap, plus NEED consistently has the biggest gap for properties that EPC assessors believe have the least insulation, or worst efficiency, similar to the finding from analysis using SERL data.

[82] Godoy, et al., Causes of poor domestic energy rating: A comparison between EPC modelled and metered energy use in 300,000 UK homes, paper in preparation, 2025.

There is little change in the performance gap for electricity with any parameter and little change in the performance gap with IMD suggesting that the performance gap is less to do with occupant behaviour and more to do with building characteristics. The change in gas but not electricity suggest that the gap is to do with heating.

Note that the consumption data contained within NEED is based on annualised meter data. For gas consumption, this is an annual quantity (AQ) which is an estimate of the amount of gas that the meter point will use in a year under seasonal normal weather conditions. The AQ is based on consumption between two meter readings. For electricity consumption, annualised estimates are based on either an annualised advance (AA) or estimated annual consumption (EAC). The AA is an estimate of annualised consumption based on consumption recorded between two meter readings. The EAC is used where two meter readings are not available, and an estimate of annualised consumption is produced by the energy company using historical information and profile information relating to the meter. To check if this process has had an impact NEED energy consumption data for the SERL homes was compared to SERL data, the results of this comparison are provided in Appendix H.

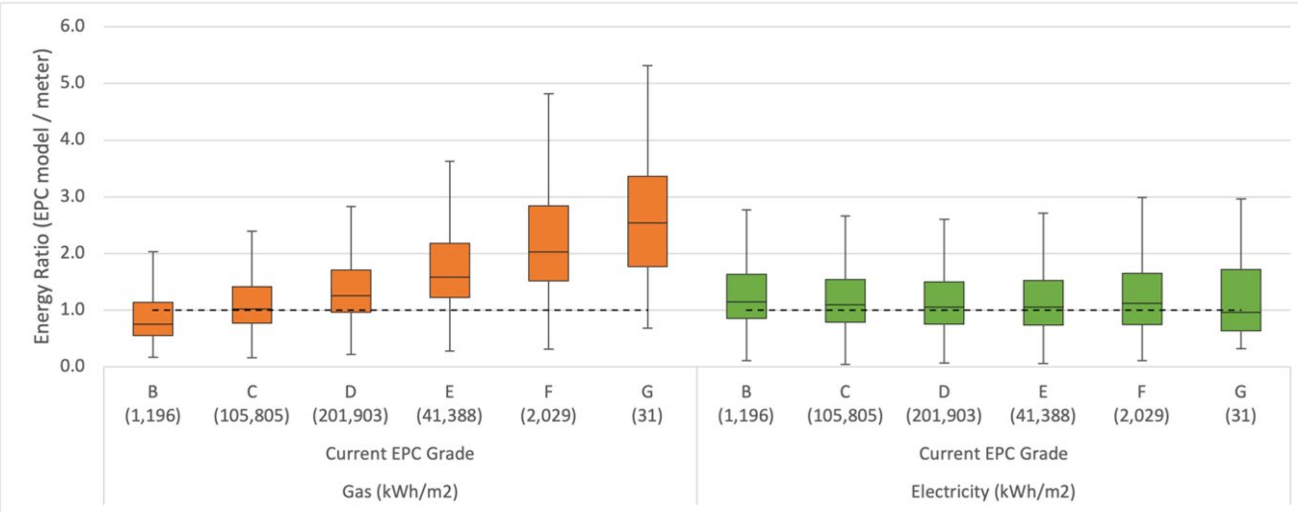

Figure 97 Variation of modelled to metered energy ratio with EPC-grade, for gas and electricity.

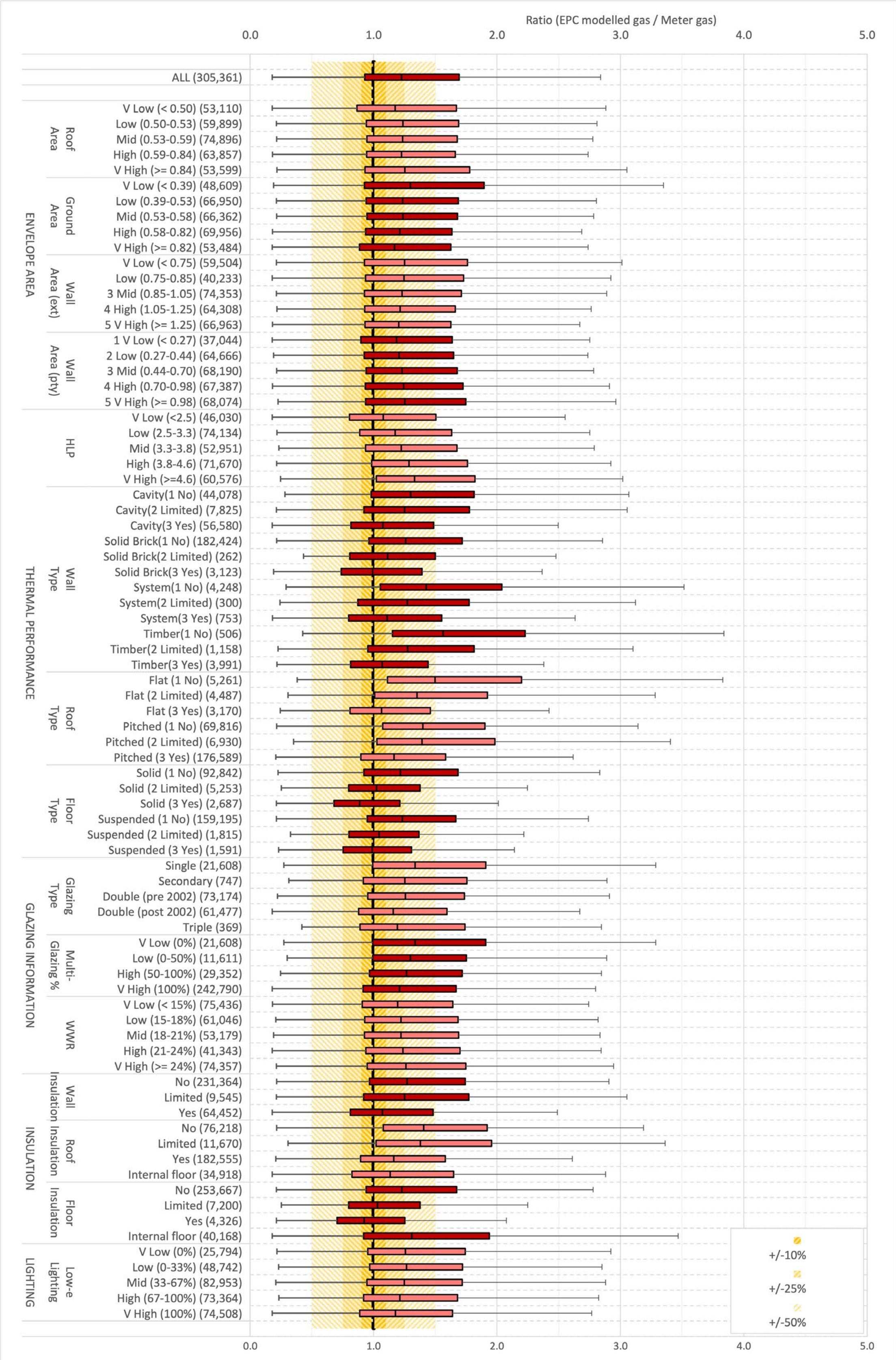

Figure 98 Distribution of the ratio of EPC modelled to metered gas intensity across different characteristics.

Appendix H: Comparison of metered annual energy consumption data from NEED with SERL data

Since NEED is based on annualised meter data which converts meter readings to annual consumption estimates, we compared the annualised values from NEED with the sum of the smart meter data over the year on a per-household basis. We matched the NEED data to the SERL sample using the Unique Property Reference Number (UPRN). The years used for this analysis followed the annual periods defined by NEED: May to May for gas data and February to February for electricity data.

For this analysis, we required 95% daily smart meter energy data availability in each month (the daily value could be the sum of the half hourly readings or a direct daily reading from the smart meter). This means a maximum of one daily reading could be missing in each month, in this case the missing data is replaced with the mean for that month.

For the electricity analysis we filtered out homes that have PV on a year-by-year basis (homes that exported electricity for 1 or more half hour period in a year were considered to have PV in that year). This is important because the electricity consumption data from NEED does not include electricity produced and consumed on site (as for smart meters) and does not record electricity exports to the grid (which are recorded separately for smart meters), so in order to investigate the most straightforward case we removed homes with PV.

We conducted this comparison for years 2020 to 2022. Figure 99, Table 27 and Table 28 below summarise the agreement between NEED and SERL for electricity consumption. This shows a notable discrepancy between SERL and NEED annualised data whereby NEED data is consistently lower than SERL data on average and has a larger standard deviation. The mean absolute error varies between 1.66 kWh/day and 2.15 kWh/day, and less than half of the data points agree within 10%. The cause of this discrepancy remains unclear at present.

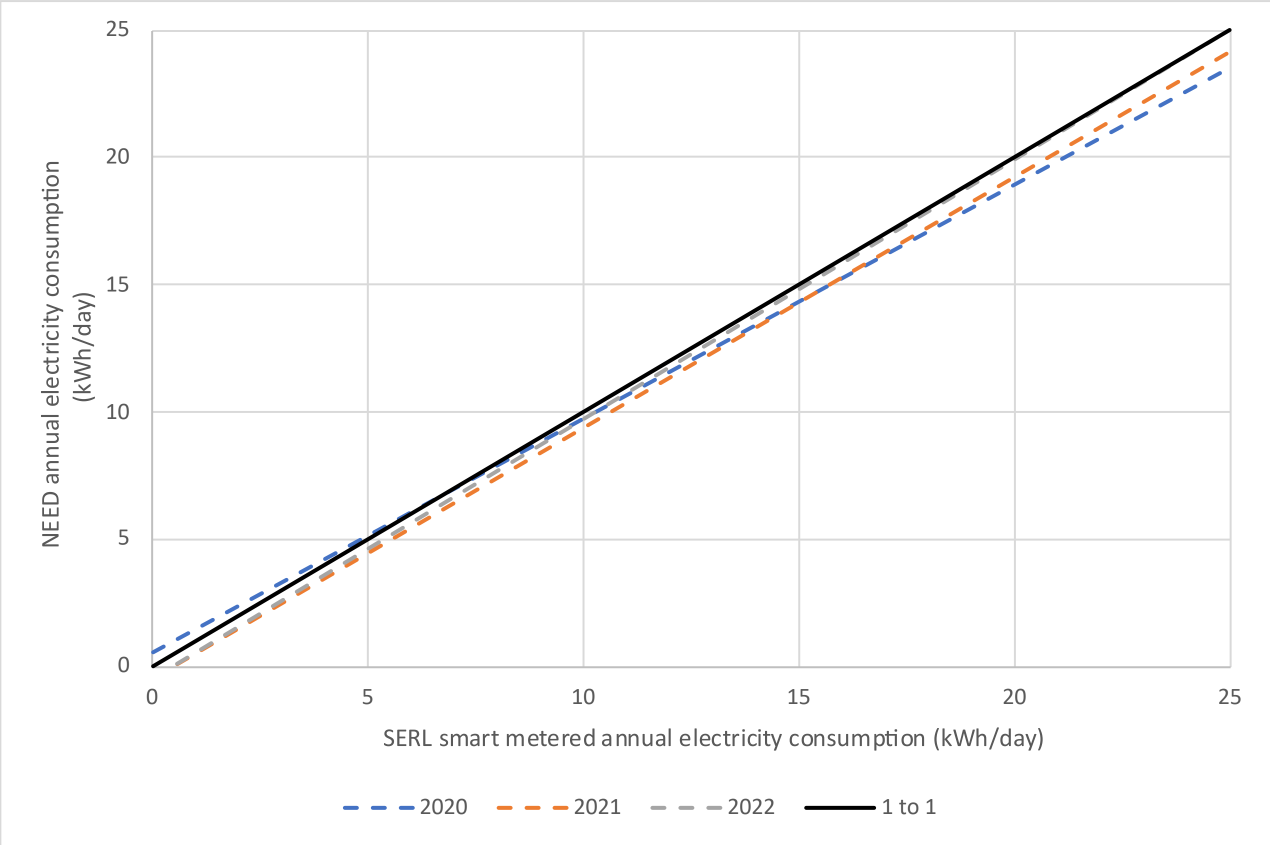

Figure 99 Best fit line between the NEED annual electricity consumption and smart metered annual electricity consumption per household for years 2020 to 2022.

Table 27 Summary of best fit line parameters and descriptive statistics for NEED annual electricity consumption and smart metered consumption per household for years 2020 to 2022.

Year	Fuel	Gradient	Intercept	SERL mean (kWh/day)	NEED mean (kWh/day)	SERL median (kWh/day)	NEED median (kWh/day)	SERL standard deviation (kWh/day)	NEED standard deviation (kWh/day)
2020	electricity import	0.92	0.61	10.30	10.04	8.68	8.02	6.77	7.44
2021	electricity import	0.98	-0.41	9.67	9.08	8.12	7.24	6.45	7.00
2022	electricity import	1.02	-0.47	8.60	8.30	7.18	6.57	5.70	6.67

Table 28 Summary of the average differences and number of households for which the agreement between the two measures is within a given percentage of the metered value for NEED annual electricity consumption and smart metered electricity consumption for years 2020 to 2022.

Year	Mean bias error (kWh/day)	Mean absolute error (kWh/day)	Mean percentage error (%)	Mean absolute percentage error (%)	N	N within 1%	N within 5%	N within 10%
2020	0.26	2.15	-8	29	3930	183	932	1751
2021	0.59	1.70	6	18	7860	304	1544	3124
2022	0.30	1.66	5	19	6957	285	1320	2774

We conducted the same comparison for gas consumption for years 2020 to 2022. NEED provides gas data on both a weather corrected and non-weather corrected basis. The weather corrected data is an estimate of what a property would consume in seasonal normal conditions and means that consumption data across the years can be compared with the impact of weather removed. Only the non-weather corrected data was compared with the smart meter data since it was not possible to apply the same weather correction as is applied to NEED to the smart meter data.

Figure 100, Table 29 and Table 30 below summarise the agreement between NEED And SERL for gas, the agreement is overall better than for electricity. Unlike electricity, gas does not show a consistent direction in the discrepancy between SERL and NEED data. SERL mean gas use is higher in 2020 and the median is higher is higher for each year analysed. For gas the mean absolute error varies between 0.89 kWh/day and 2.40 kWh/day, and over 90% of data points agree within 10%. Note that Table 30 shows relatively large magnitude percentage errors in 2021, this is because of a handful of cases where either the SERL or NEED data is close to zero while the opposite data source is not, thereby considerably skewing the percentage values for these cases.

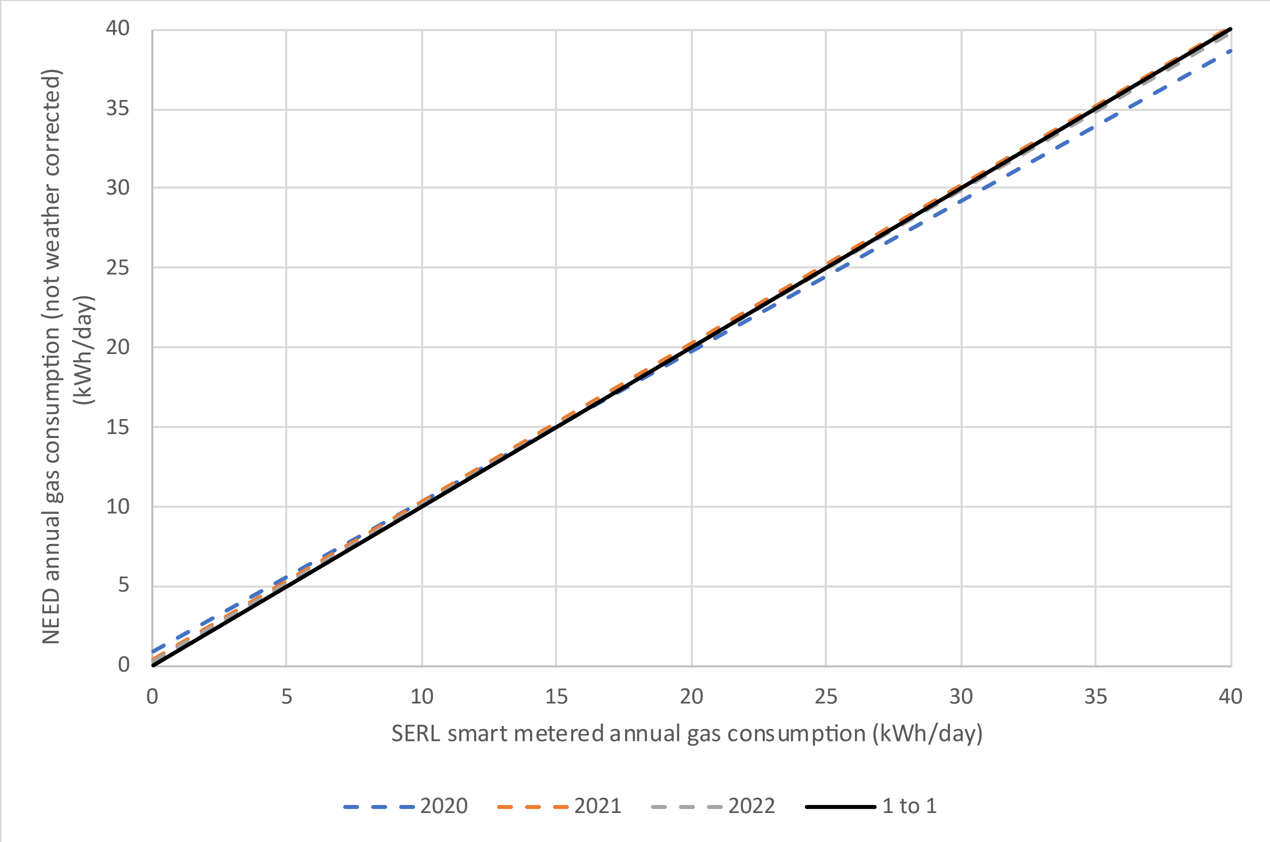

Figure 100 Best fit line between the NEED annual non-weather corrected gas consumption and smart metered annual gas consumption per household for years 2020 to 2022.

Table 29: Summary of best fit line parameters and descriptive statistics for NEED annual gas consumption (non-weather corrected) and smart metered consumption per household for years 2020 to 2022

Year	Fuel	Gradient	Intercept	SERL mean (kWh/day)	NEED mean (kWh/day)	SERL median (kWh/day)	NEED median (kWh/day)	SERL standard deviation (kWh/day)	NEED standard deviation (kWh/day)
2020	Gas	0.94	0.97	41.17	39.69	37.48	36.08	22.86	22.20
2021	Gas	0.99	0.45	32.97	33.16	29.62	29.50	19.29	19.96
2022	Gas	0.99	0.28	29.06	29.03	26.01	25.95	17.61	17.73

Table 30 Summary of the average differences and number of households for which the agreement between the two measures is within a given percentage of the metered value for NEED annual gas consumption (non-weather corrected) and smart metered gas consumption for years 2020 to 2022.

Year	Mean bias error (kWh/day)	Mean absolute error (kWh/day)	Mean percentage error (%)	Mean absolute percentage error (%)	N	N within 1%	N within 5%	N within 10%
2020	1.48	2.40	1.9	7.1	4928	364	3564	4508
2021	-0.19	1.35	-10.3	13.9	5756	1845	5066	5457
2022	0.06	0.89	-0.5	4.2	6334	2068	5712	6064

Appendix J Background to Mean Internal Temperature SAP calculations

Within both SAP and BREDEM models, the Mean Internal Temperature (MIT) feeds directly into the calculation for the dwelling’s space heating requirement. For this reason, the performance gap may be attributable to variables that relate to the calculation of the dwellings MIT. The calculation of the dwelling MIT is discussed below along with some key assumptions highlighted. A selection of these variables are discussed below, with reference to SAP 2012, version 9.92 and BREDEM 2012.

The underlying methodology to estimate the seasonal energy requirement for dwellings, under assumed occupancy conditions and with standard regional weather conditions is described in the Standard Assessment Procedure (SAP) and BREDEM. In the case of SAP 2012, this methodology is laid out over approximately 30 pages which describe the range of factors that contribute to the overall score as well as the conventions and principles of the procedure.

SAP is designed for dwellings that are self-contained of any age and size. In the case of flats and mixed-use units, it applies to individual dwellings and not to shared or common areas such as corridors which are assessed using procedures for non-domestic buildings.

Standards referred to within the document are provided which describe the calculation methods for thermal resistance and transmittance of building elements (BS EN ISO 6946), hygrothermal properties (BS EN ISO 10456), among others. Following this is the SAP worksheet itself, which details the inputs and algorithmic procedure to calculate the SAP score. As such, this section contains many underlying relationships in SAP, however it extensively references Appendix A to U which contain procedures and principles used to determine inputs into the main worksheet. Further guidance and relationships used within the calculations are found in tables 1 to 16. Some of these will be included in the following discussion as they are directly related the calculation of MIT.

Referenced within SAP are key papers which describe some of the original thinking and principles behind the model, including Anderson et al., (1985)[83]. Anderson et al., (1985) reference Uglow (1981)[84], in which an initial energy balance model for a domestic building (BREDEM-1) is proposed, which calculates the energy balance of a dwelling based on the MIT, the solar and incidental gains, and energy required for cooking, hot water, lighting, and appliances. The MIT was calculated using a simple steady state model which included internal and external mean temperature, U-values and area of fabric elements, and the specific heat capacity and density of air, along with the volumetric air change rate. The ventilation heat loss term was also expressed as 1/3nV, with V being the volume of the dwelling and n being the air change rate. This air change rate was thought to be of the order of 1ach for typical dwellings and values ranging from 0.5ach for well-sealed dwellings to 2ach for leaky dwellings in exposed positions were proposed.

BREDEM-1 was validated on the basis of 42 dwellings within a 40 mile radius of Garston in Hertfordshire, see Uglow (1982)[85]. These dwellings were owned by members of BRE, and participants were asked to provide quarterly energy statements as well as respond to a questionnaire. This questionnaire included questions related to the dwelling construction (including curtain type and internal wall type), information about the heating system including the times that heating was used and any supplementary heating, and information about incidental gains including cooking, occupant number and when the dwelling was typically occupied, and the use of appliances. This information was then used to select entries from tables contained in Uglow (1981), which contained initial reference values for seasonal MIT based on insulation level, heating patterns, and the proportion of the dwelling that was heated. These MITs were then used to calculate the daily energy balance based on the total heat loss over 24 hours due to conduction through building elements and due to ventilation.

This meant that despite being in possession of the actual heating times, the calculation made use of an early version of SAP 2012 9.92 table 4e (see Figure 101) below. This has two heating schedules, and three possible levels of insulation, as well as full, partial, or not centrally heated.

Interestingly, this model resulted in an approximate 14% overprediction of energy use, with the worst agreement between modelled and measured energy consumption being four dwellings

[83] Anderson, B. B., Clark, A. J., Baldwin, B., & Milbank, N. O. (1985). BREDEM-BRE Domestic Energy Model: background, philosophy and description.
[84] Uglow CE. The calculation of energy use in dwellings. Building Services Engineering Research and Technology. 1981;2(1):1-14. doi:10.1177/014362448100200101
[85] Uglow CE. Energy use in dwellings: An exercise to investigate the validity of a simple calculation method. Building Services Engineering Research and Technology. 1982;3(1):35-39. doi:10.1177/014362448200300105

which had the following characteristics: they were all ‘poorly heated’, and had electric heating. 3 of the 4 were flats and all 4 had a single occupant.

The hypothesised causes of the overprediction were: assumed MIT too high (underheated dwellings), assumed heating system efficiency being too low, assumed incidental gains too low, assumed value of air infiltration too high, and lastly that the actual fuel consumption was not derived correctly from the quarterly statements.

Table 4 Mean internal temperatures
The following daily mean internal temperatures are suggested for use in equation (1). Values are averaged over the dwelling and over the heating season; they are based on a structure of medium weight and should be increased by 1°C for a heavyweight structure, reduced by 1°C for a lightweight structure.

The assumed heating regimes are:
(1) Heating provided from 0600 to 2300
(2) Heating provided from 0600 to 0900 and 1700 to 2300

The three insulation standards are:
(A) No additional insulation
(B) Loft insulation only
(C) Loft and cavity fill insulation

Heating system	Heating regime	Insulation standard	$\bar{t}_i$ (°C)
Full central heating	1	A	17.5
		B	18.0
		C	19.5
	2	A	16.5
		B	17.0
		C	18.5
Partial central heating	1	A	16.0
		B	16.5
		C	18.0
	2	A	15.0
		B	15.5
		C	17.0
Not centrally heated	1	A	14.5
		B	15.0
		C	16.5
	2	A	13.5
		B	14.0
		C	15.5

Figure 101 Reproduction of Table 4 from Uglow (1981), showing the assumed heating schedule and the possible insulation standards, along with the internal temperatures that these combinations of variables were associated with.

A later study, Firth et al. (2009)[86], performed a sensitivity analysis on the Community Domestic Energy Model to assess key determinants of domestic energy use, the top three (in order of influence) were the demand temperature, and the length of the daily heating period, and the external air temperature. Average story height, floor area, and boiler efficiency were also influential.

BREDEM and SAP have undergone many changes. Notably, from an initial single zone model in BREDEM-1 to a 2-zone model in BREDEM-2, and to include the effect of energy saving measures. At present, the model is undergoing further review, and a new model, HEM, is being developed that will be able to account for dynamic effects. To help frame the present investigation of the SAP temperature model as it stands key variables and elements of the calculation are highlighted in Table 31 below.

Table 31 Summary of the key variables and elements of the temperature calculation in SAP.

Variable (No. in SAP table)	Source	Notes and uses
Fabric heat loss (37) (element-wise)	Calculated from a number of parameters that are inputted including the thermal transmittance (U-values) and surface areas of building elements, specific heat capacity, and Psi values for thermal bridging. If construction details are not known then default values for the Thermal Mass Parameter from Table 1f can be used.	Used to calculate the HTC and in cooling load calculations
Heat Loss Parameter (40m)	Calculated as HTC÷floor area per month	Heat Loss per square meter per degree of temperature difference between indoors and outdoors.

[86] Firth, S. K., Lomas, K. J., & Wright, A. J. (2009). Targeting household energy-efficiency measures using sensitivity analysis. Building Research & Information, 38(1), 25–41. https://doi.org/10.1080/09613210903236706

		Used to calculate the Zone 2 temperature reduction as well as the utilisation factor for heating (Table 9a).
HTC (39m)	Calculated as the sum of fabric and ventilation heat losses	Used in multiple parts of SAP, including to calculate the utilisation factor for heating,
Heat loss rate for a given MIT (97m) x Num days in month (41m)	= HTC*(monthly adjusted MIT – Monthly average external temperature)	Critical parameter to calculate space heat demand.
Mean internal temperature in living area T_1 (87m)	Calculated in Table 9	The average temperature in the main living space. Influenced by heating patterns, gains, and losses, the HLP as well as the cooling time for the building, the heating system responsiveness, and others.
Monthly average external temperature (96m, Table U1)	Default regional weather variables from BRE	Used in the MIT calculation.
R: responsiveness of main heating system	Table 4a or 4d	The responsiveness of the heating system describes how quickly the heat output of the system drops to zero when it is turned off and is used to calculate the temperature reduction when the heating is off.
Monthly Space Heating Requirement 98m	Calculated from monthly heat loss (based on the monthly MIT) offset by useful gains, which are derived from the utilisation factor and the total gains.	Larger difference between indoor and outdoor temperature result in greater demand, in SAP this is a linear relationship.
TMP (35)	TMP = heat capacity ÷ floor area, or from table 1f. Used in the	Default values are for low, medium, or heavyweight

	calculation for the utilisation factor (and therefore space heating requirement) and the temperature reduction when the heating is off.	buildings (100, 250, 450 kJ/m²K respectively).
T_h = Demand temperature (Table 9)	For the living area (Z1) the demand temperature is 21°, and elsewhere (Z2) the demand temperature is 21-0.5HLP, 21 – HLP + HLP² / 12, or 21 – HLP + HLP² / 12 depending on the heating control type (Table 4e)	There is a maximum HLP of 6 for the purposes of the Z2 temperature calculation, which means the there is a maximum temperature reduction of 3°C.
Total Gains (84m)	Total of Solar and internal gains per month (W). Calculated from both default and building specific parameters.	
Useful gains (95m)* number days in month 41m	Total Gains multiplied by the utilisation factor	
Vent heat loss (38m)	Monthly heat loss due to ventilation, calculated on the basis of an effective air change rate and dwelling volume. The effective air change rate is based on either a pressurisation test or the sum of infiltration contributions through different elements for monthly average wind speeds (table U1).	For naturally ventilated dwellings (which form the majority in the UK) there is a minimum of 0.5ACH required by Part F of the approved documents, which is translated into the SAP calculation. On top of this are further contributions for the infiltration through building components observed by the SAP Assessor (such as chimneys, how sheltered the building is, and a number of other parameters). See page 179 of SAP 2012. For dwellings that have a pressurisation test

		result available the divide by 20 rule is used. See Roberts et al., for a discussion of the challenges in using this method to convert to a ventilation rate.
η= utilisation factor	Calculated in Table 9a on the basis of a number of intermediary parameters, including internal and external temperatures, a time constant (calculated as TMP/3.6*HLP), the ratio of gains to losses, 'a' which is a modifier for the time constant (a = 1 + τ / 15), and lastly τ= TMP/HLP.	The utilisation factor provides a method to estimate how efficiently gains are used.
u1and u2: Temperature reduction in Zones 1 and 2 respectively	Calculated in table 9b on the basis of the time constant above, the time for which the heating is off, the responsiveness of the heating system (taken from table 4a or 4d), demand temperature during heated period for each Zone, the living are fraction, and the temperature without heating.	

The region variable is important because SAP includes normative climate data (Table U1-3, including mean monthly external temperatures, Global Horizontal Irradiance, and wind speed) for 21 regions as well as a UK average. These are then used to calculate the solar gains, ventilation rates, and the heat demand for specific buildings. At the outset, there was a single region for all dwellings, perhaps because this created a fairer comparison for fabric efficiency and energy demand, however, a disadvantage of this approach was that the costs involved in heating a dwelling, which does have a specific location, would not be accurately represented. Hence, regional data for a representative design year is used in order to provide an estimate of the actual cost of running a particular dwelling.

The Standard Assessment Procedure (SAP) assumes that buildings are operated according to standard conditions, which include a heating schedule which assumes a set of standard occupancy conditions. It is further assumed that dwellings will be heated to a comfortable temperature, which is defined within SAP (noting that there are differing assumptions and methods associated with different versions of SAP) to be 21 degrees in the living area, with an assumed difference between the living area and the rest of the dwelling. This difference is calculated on the basis of the dwelling Heat Loss Parameter. Occupancy is scheduled differently depending on whether it is a weekday or a weekend day. This means that heating is assumed to be operating between 7am and 9 am, and 4pm and 11pm during the week, and 7am to 5pm at the weekend. These assumptions are applied for the whole heating season, which is defined as being from October to May inclusive. A further complication is the inclusion of a secondary heating system, which is assumed to be present (and by implication used) under certain conditions and in certain areas of the dwelling.

Heating is assumed to be either “on” or “off” according to the assumed heating schedule that the dwelling is operated in. This heating schedule determines the number of hours for which the heating is off, according to the day of the week. For weekdays, the heating is assumed off for a total of 15/24 hours (from 9am to 4pm, and 11pm to 7am), and for weekend days the heating is assumed to be off for 8 hours (between 11pm and 7am), and depending on the heating system responsiveness parameter will cool at different rates.

Table 9 in sap 9.92 provides the heating pattern on which the calculation for the MIT is based. There is an assumed heating schedule, and a demand temperature of 21°C in the Living Area. The temperature in the rest of the dwelling is assumed to be less than the demand temperature by a factor that is dependent on the building heat loss parameter (HLP), and the heating control type. The heating control type is either 1,2, or 3, and comes from Table 4e (p210 SAP 2012 9.92), which describes heating systems and their operational controls. Much diversity of heating system and user control settings including presence of thermostatic controls, programmers, TRVs, among others is then compiled into a relatively few parameters for the purposes of the MIT calculation.

The logic of the inclusion of control categories is to better capture how control of heating system can influence the amount of energy required to heat the dwelling. The key assumptions are that a lack of control will effectively increase the demand temperature, so systems without thermostatic controls are penalised. Next, a lack of thermostatic controls means that the heating system will not switch off once the demand temperature is reached, which reduces the overall efficiency of the system. A lack of control of Zone 2 temperature is assumed to increase the amount of ‘overheating’ in Zone 2, and conversely independent control of Zone 2 is assumed to imply a shorter heating period for Zone 2, with a corresponding drop in energy consumption (see Anderson et al, 2002[87])). However, it is not clear that the underlying logic for these control mechanisms applied in SAP is consistent with the way that people heat their

[87] Anderson, B. R., Chapman, P. F., Cutland, N. G., Dickson, C. M., Henderson, G., Henderson, J. H., Iles, P. J., Kosmina, L., & Shorrock, L. D. (2002). BREDEM-12 Model description: 2001 update. BRE. ISBN 1 86081 536 7

dwellings today, or how the benefit of fine control of heating systems is taken up by occupants or heating systems.

For example, Huebner et al. (2014)[88] performed a cluster analysis on temperature data gathered from 275 English homes and was able to identify four distinct profiles which differed in their maximum and minimum temperatures, as well as in how temperature varied throughout the day. Furthermore, only 40% of the homes showed a bimodal heating pattern (which is assumed in SAP), with 60% having different profiles. Lomas et al., (2018)[89] performed a critical review of the literature for energy savings associated with heating system control and reported that on the whole there was limited evidence to support claims about energy savings associated with different control types, although when used correctly, zonal controllers that heated different spaces at different times could result in energy saving. On the other hand, some evidence was also found that smart thermostats do not result in energy savings and may actually increase energy demand. SAP also assumes that the temperature level required by the occupant is independent of the structure of the building, occupants, and the efficiency of building elements (see for example Anderson et al, 1985).

Depending on the Control Category then, the Zone 2 temperature is then 21 minus half of the HLP, or 21 minus the HLP + (HLP^2)/2. This effectively places a maximum temperature reduction of 3 degrees for zone two. However, the EFUS thermal comfort, damp and mould report found that for the winter of 2017/18, although living rooms were warmer than hallways and main bedrooms, the differences were not large; mean monthly temperatures for different rooms indicated that living rooms were 0.4°C warmer than hallways, and 0.5°C warmer than main bedrooms, with third bedrooms being on average 0.8°C cooler. It is therefore of interest to assess the difference in measured monthly MITs for Zone 1 and 2 against their SAP model equivalents.

Appendix K: Forensic investigations interview proforma

Note that our primary year of analysis is 2021, so changes before or during 2021 are particularly important.

Introduction

Thank you for agreeing to take part in this research, we would like to ask a few questions about any changes in your home over the last few years – particularly before or during 2021, about how you use the heating and hot water and any other significant energy uses. These questions are just to help us with our research, but you don't have to answer any questions

[88] Huebner, G. M., McMichael, M., Shipworth, D., Shipworth, M., Durand-Daubin, M., & Summerfield, A. J. (2014). The shape of warmth: temperature profiles in living rooms. Building Research & Information, 43(2), 185–196. https://doi.org/10.1080/09613218.2014.922339

[89] Lomas, K. J., Oliveira, S., Warren, P., Haines, V. J., Chatterton, T., Beizaee, A., Prestwood, E., & Gething, B. (2018). Do domestic heating controls save energy? A review of the evidence. Renewable and Sustainable Energy Reviews, 93, 52–75. https://doi.org/10.1016/j.rser.2018.05.002

you do not want to, and you don't have to give any reason. Do you have any questions before we begin?

Note of any questions:

Home history

We are interested in whether there have been any major changes in your home since you moved in, this is because if there have been any significant changes in energy use over time it can helps us to understand why that might be happening. Could you tell me when you moved in and any major renovations since then? (e.g. any insulation, window replacement, changes to central heating etc)

Year moved in:

Major renovation (e.g. new boiler, double glazing, loft insulation)	Replaced (e.g. system boiler, single glazing)	When replaced (year of change if possible, otherwise pre/post 2021)

Occupancy

We're interested in typical occupancy patterns to help understand and explain energy use patterns over time.

Could you tell me how many people live here at the moment?
Have there been any changes in occupancy over the time you have lived here, for example has anyone moved in or out or have there been any new babies since then?
And do you have any pets?
In a typical week when is the house typically occupied with at least one person at home?

	Weekday	Weekend
Typical week (term-time if have school age children)		
School holidays (if have school age children)		

Typical heating use in winter

We're interested in how the heating is used as it's important for understanding overall energy use.

Do you have a thermostat to control the heating?
If yes: typical thermostat temperature during winter:
If no: how is the heating usually controlled?
Typical heating hours in winter:
Any rooms not heated? Which ones?
Any secondary heating and fuel sources:

Typical heating use in autumn and spring

Typical thermostat temperature during autumn and spring (e.g. September-October, March – May):
Typical heating hours in autumn and spring:
Any rooms not heated? Which ones?

Appliances

Do you have any air conditioning?
If yes: when did you get it? And when do you typically use it?
Any electric vehicles which are charged at home?
If yes: when did you get it?
And how much are they typically charged?
Do you use any appliances with particularly high energy consumption? E.g. very big freezers, fish tanks, etc?

Typical cooking

We're interested in energy use for cooking.

Do you use both gas and electric for cooking (hob and oven)?
If both: would you say you use either gas or electricity for cooking much more than the other overall, or do you use both a similar amount?

Typical hot water use

We're interested in hot water use as part of overall energy use.

Firstly, how is the hot water for baths/showers heated? E.g. from the boiler / electric shower?

Thinking of a typical week…

Typical number of showers or baths in a week:
Typically how long are the showers? E.g. less than 5 minutes, 5-15 minutes, >15 minutes.
Is there anything else that uses a significant amount of hot water in your house (excluding any dishwashers or washing machines as these almost always heat their own water)

Ventilation

Do you typically open windows in the winter? And if so, when? (e.g. prompt with cooking, shower, sleeping, mornings, etc)
How wide would you usually open windows when you do this, and for how long?
What about in the autumn /spring?
Do you use anything else for airflow or ventilation in the house? Like any extract fans?

Appendix L: Summary of the Forensic Surveys

Introduction

A total of 45 forensic surveys were carried out, broken down as follows:

37 gas heated homes with RdSAP EPCs
4 new build gas heated homes with full SAP EPCs
4 electrically heated homes with RdSAP EPCs

In each case, full SAP data was collected on the property and an interview was held with the occupant to establish the pattern of energy use in the home (focussing on 2021) and the details of improvement measures carried out since they had been living there. An attempt was also made to collect some of the additional information that may be needed for the new Home Energy Model that is being developed to replace SAP.

Following each survey, the details were entered into SAP 2012 software to model the energy performance:

As surveyed in 2024/5
As in 2021 (if different from in 2024/5 due to improvement measures installed since 2021)
As in the EPC, with input data edited to match the EPC input data and the energy efficiency rating (EER) result as closely as possible. (With just one exception, it was possible to replicate the EER from the SAP 2012 assessment to the same as shown on the EPC, once rounded to the nearest integer).

The ‘as in 2021’ versions were also imported into SAP 10.2 software to provide a comparison of the results from SAP 10 with those from SAP 2012.

Analysis of differences between ‘as 2021’ assessments and ‘as EPC’ assessments

In all cases there were a number of differences between the SAP input data collected in the forensic surveys and the input data (and RdSAP defaults) used to produce the EPC.

The details that needed to be revised in the SAP data from the ‘as 2021’ assessment to create the ‘as EPC’ assessment were recorded and classified into five categories:

SAP core processes
RdSAP core processes
RdSAP conventions
Assessor errors
Measures installed since the EPC was issued

The impact of these issues on the EER and the estimated kWh/year for space heating and hot water was assessed individually and as a category, as percentages compared to the ‘as EPC’ assessment as a baseline. Note that in many cases the impacts opposed each other resulting in a relatively small change in the overall results.

The issues that we identified are presented in Table 32.

Table 32 Issues associated with the SAP core processes

	No.	Impact on kWh/year	Comments
Cannot allow for the instantaneous electric shower	2		Can only be modelled if all hot water is electric instantaneous. Reduces energy use and reduces EER. Will still apply in RdSAP 10.

Cannot allow for significant use of portable electric heaters	1		Could be modelled as second main heating. Reduces energy use and reduces EER.
Default air permeability of 15m3/m2h@50Pa for new build instead of pressure test	1	-8.35%	Does not apply for SAP 10/Part L1 2022

There was also one property (F1) with a 'Quooker' tap in the kitchen that provides hot water to the kitchen sink and is effectively a secondary electric instantaneous hot water heater. This can not be modelled in full SAP or RdSAP as there was also a combi boiler present.

Recommendations:

> Enable multiple shower types to be accounted for in RdSAP 10. The number of showers is already required so this would not take significantly more time to process. Consider whether other secondary hot water systems, such as 'Quooker' taps, should also be modelled in SAP/HEM.

Table 33 Summary of issues associated with RdSAP core processes.

	No.	Impact on kWh/year	Comments
The measured window areas total less than the RdSAP default.	14	-1.74% to 5.03%	Can be significant but in most cases the impact is less than 1% as reduced heat loss is offset by reduced solar gains. Will not apply to RdSAP 10.
The measured window areas total greater than the RdSAP default.	20	-1.57% to 2.02%	Can be significant but in most cases the impact is less than 1% as increased heat loss is offset by increased solar gains. Will not apply to RdSAP 10.

The measured living area is less than the RdSAP default based number of habitable rooms.	26	-2.50% to -0.18%	Still applies to RdSAP 10, although there will be the option to enter the living area fraction based on measurements.
The measured living area is greater than the RdSAP default based number of habitable rooms.	7	0.23% to 5.60%	Still applies to RdSAP 10, although there will be the option to enter the living area fraction based on measurements.
Changes in RdSAP defaults for wall U-values implemented from v9.93.	9	-4.86% to -8.71% for solid walls, -1.35% for cavity wall	If EPC was issued using v9.91 or 9.92. Generally better U-values (e.g. 1.7 instead of 2.1 for solid walls) but filled cavity worse U-value (0.7 instead of 0.5)
Sloping ceiling areas ignored by RdSAP	7	0.72% to 6.99%	Usually ‘dropped eaves’ where wall height >1.8m
Oriel window ignored by RdSAP	5	0.87% to 2.94%	
Lower performance of walls to garage not accounted for	4	0.30% to 6.54%	This is where the wall construction is different from the main external wall
Boarded loft area not accounted for	3	0.35% to 0.68%	Treated as remainder of loft (insulated). With 100mm insulation below boarding. Would be more significant if assumed uninsulated. (On reflection these should probably have been classified under RdSAP conventions rather than core processes).
Incorrect heat loss areas for room in the roof from RdSAP formulae	2	-8.93% to 2.18%	Improved procedures in RdSAP 10 will improve this.
Extract fans present that will not have been included in the EPC data	2	-0.81% to 0.56%	Number of extract fans will be recorded in RdSAP 10.

Different thickness of solid brick walls	2		Additional options in RdSAP 10 will improve this.
Draught lobby not accounted for in RdSAP	1		Will be included in RdSAP 10

Recommendations:

Require the living area fraction based on the number of habitable rooms to be displayed in the software with a requirement to over-ride this with the measured value if it appears too high or low when looking at the floor plan.
Enable an 'alternative roof' to be entered into RdSAP 10 when there is a sloping ceiling that is not a 'room in the roof' and where a partially boarded loft is assumed to have no insulation below the boards. (The need to create an artificial extension to deal with these is unduly onerous and likely to lead to errors).
Require walls to integral garages to be treated as alternative walls in RdSAP (as in full SAP and as for walls to corridors in blocks of flats). The wall construction is often different and less well insulated than the main external walls. In other cases, the effective U-value is better due to the shelter factor. In the six examples we surveyed, the percentage of the total external wall area made up of the walls to the garage were all between 10% and 20%, so should not have been ignored according to the '10% rule' in convention 2.13.

Table 34 Summary of issues associated with RdSAP conventions

	No.	Impact on kWh/year	Comments
Windows classified as pre-2002 due to lack of date evidence.	1	-1.56%	Owner confident that windows are post-2002, although no documentary evidence (convention 3.12a requires 'unknown' date if no evidence).
No loft insulation assumed in EPC calculation but there is 100mm below boarding	1	-13.75%	Convention 3.04 requires loft insulation to be recorded as 'unknown' where there is doubt about insulation below boarding. Conclusive evidence is often difficult to obtain.

Heat loss wall to side due to stepped terrace is ignored	1	2.19%	Convention 2.23 allows this when the height of the heat loss wall is <25% of the room height. It is just over 10% in this case.
Heated conservatory included	1	1.48%	Radiators in conservatory. Impact relatively low since solar gains offset heat losses.

Table 35 Summary of issues associated with assessor errors

	No.	Impact on kWh/year	Comments
Significantly different floor area from forensic survey measurements.	16	-13.16% to 18.81%	Often over 5% discrepancy in energy use despite very small impact on EER.
Bay not included as an extension (so ignored in EPC data)	9	0.19% to 2.16%	Impact depends on size of bay and how much construction or age differs (sometimes just roof heat loss ignored).
Extensions not defined	9	-14.64% to 6.87%	Sometimes two or three in one property. Negative if newer age band than main part. Impact low if just different floor type or small area of exposed floor.
Incorrect property age band	8	-36.84% to 5.52%	Impact very small in 4 of the cases. Property owners usually know – maybe more difficult if properties assessed when void.

Incorrect age band for extension	6	-6.86% to 2.78%	Some may have been defaulted to same as main building age band due to lack of evidence. We were able to confirm some by on-line research (which the DEA could also have done)
Loft insulation thickness wrong	6	-21.8% to 1.79%	Three cases significant where no insulation was recorded. The other three relatively small impact.
Incorrect number of habitable rooms	4	-0.89% to 0.79%	Low impact but adds to the case for measuring living area.
Default efficiency used for boiler	4	-12.44% to -4.62%	
Single glazed window(s) not included in EPC data	3	1.26% to 2.25%	
Secondary heating incorrectly classified or omitted	3	-15.13% to 2.14%	
Omitted/incorrect thermal bridging details	3	-1.62% to 0.87%	Only applicable to new build EPCs. Applies to all three full SAP EPCs where thermal bridging details were entered. (The fourth used the default y-value).
Incorrect U-values entered	3	-27.36% to 3.80%	Two are new build, so may be incorrect information provided by the developer.
Sheltered walls not included in EPC data	3	Up to 3.81%	This applies to 3 of the 5 flats surveyed.

Significantly different room heights from forensic survey measurements.	2	6.41% to 6.57%	Both properties with high ceilings.
Incorrect boiler selected from database	2	-0.65% to -0.32%	One was new build so could be incorrect information provided by the developer
Room thermostat and/or cylinder stat not included in EPC data	2	-5.34% to -3.18%	
Boarded loft area not accounted for	2		40% of loft area in one case but impact low as 100mm below.
Incorrect ventilation details in EPC data (new build)	2	-3.41% to 0.94%	New build only to date but will be included in RdSAP 10
Garage or unheated store accessed from outside included in floor area	2	-11.17% to 4.69%	One of these was also included in the “significantly different floor area category” as this contributed to this but wasn’t the only reason for it.
Room in the roof not accounted for	1	0.98%	Impact is compared to actual measurements, not the RdSAP assumptions. Using the RdSAP assumptions might have led to a greater discrepancy.
Dry lined walls not accounted for	1	-1.28%	
Incorrect energy tariff used (electric heating)	1	0.01%	No impact on energy use but large impact on EER

Incorrect classification of storage heater type	1	-4.51%	
Incorrect glazing gap	1	-0.46%	12mm instead of 16+mm

Recommendations:

- Cross check floor areas against estimates from other sources (e.g. previous EPCs, estate agent details)
- Allow alternative roofs and alternative floors to be defined in RdSAP to provide flexibility to model these more easily than by defining an extension.
- Require DEAs to confirm they have checked online for any dating information for the property or its extensions.
- Consider defining a less pessimistic default efficiency for a condensing boiler (currently 84% whereas most are close to 90%).

Measures installed since EPC issued

35 of the 45 properties visited for forensic surveys had measures installed since the EPC was issued and prior to 2021. Those that didn't have any improvements included all four new build homes, and two of the four electrically heated homes.

In most cases these led to reduced estimated energy use and/or better EERs. Table 36 summarises these (note that the impact has not been separately assessed in most cases).

Table 36 Summary of the measures installed since the EPC was issued

	No.	Comments
Low energy lights increased to 100%	23	Impact generally <1.0% kWh/year and no greater than the row below as often starting above 50%.
Low energy lights increased to <100%	10	In five of these cases, they have 100% low energy lights as surveyed but 50% was assumed for 2021 as residents said they replaced them gradually and were not sure how many there would have been in 2021.
Replacement boiler	14	Not a significant change in four cases where the previous boiler was a condensing boiler

		selected from the PCDB. Of the others, eight were replacing non-condensing boilers and two were replacing un-named condensing boilers (i.e. SAP default efficiency assumed).
Window replacement	10	Often just some windows rather than all of them. Impact -2.02% kWh/year in one case.
Controls upgrade	8	Carried out with boiler replacement in all except one case.
Loft insulation topped up	5	Not always all the loft/roof area.
Secondary room heater removed	5	Impact -8.36% kWh/year in one case.
Cavity wall insulation	4	Some areas not treated due to access issues in one case.
Internal wall insulation	2	Both were to a relatively small proportion of the total external wall area.
Chimney(s) blocked	2	
Extension to property	2	In one case (C2) floor area was increased by 46%, but energy use was lower due to other improvements. In the other (C5) there was a 35% increase in floor area and energy use increased.
Hot water cylinder jacket	1	Only thirteen of the 45 properties surveyed had cylinder based hot water systems.
Secondary glazing added	1	Just to some single glazed windows with historical character.

There were seven properties with solar PV (and in six of these cases, batteries) but with one exception these were installed since 2021.

There were four properties with other improvement measures installed since 2021 (not included in the table above). These included two extensions, one boiler replacement, one loft insulation top-up, one window replacement and one hot water cylinder with immersion replaced by electric instantaneous hot water.

There were a few cases where there were changes that reduce the EER and/or energy efficiency as summarised in Table 37.

Table 37 Summary of the cases where changes since the EPC reduced the EER and or energy efficiency.

	No.	Impact on kWh/year	Comments
Part of loft area boarded, or loft insulation reduced.	4	0.53% to 3.93%	Highest impact where 50% of loft boarded.
Gas fire or wood stove installed as secondary heating	3		Installed with other measures so the results improved overall.
Storage heaters replaced by on-peak electric systems.	2	-15.45%	Energy use reduced but energy cost increased. Impact on EER greater than impact on kWh/year. In one case the hot water cylinder was also replaced with an instantaneous system and the impact was -27.98% kWh/year.
Fewer low energy lights	1		Down to 33% from 100%. This was a new build EPC.

There was one other case where there were fewer low energy lights, but this was just one lamp (100% reduced to 92%) and this was assumed to be an assessor error. There were ten homes where the number of low energy lights was unchanged, but 9 of these were already at 100% when the EPC was issued. Over 80% of the homes surveyed had 100% low energy lights and the majority of these were LEDs.

Recommendations:

Enable EPCs to be updated when there is evidence of improvement measures having been installed. To be reliable for insulation measures, the area treated will be needed as well as the type of measure(s) installed.

Require EPCs to be updated if the property has been extended (at least when offered for sale or rent if not straight away).

Comparison of results from SAP 10 and SAP 2012

The EPC Accuracy project has focussed on comparing versions of SAP 2012 with monitored data, this is because all SERL sample homes were EPC surveyed using the SAP/RdSAP 2012 methodology. Additional work would be required to undertake a detailed comparison between SAP10 predictions and metered data, using NBM-SERL running SAP10. However, as part of the Forensic analysis properties have undergone a SAP10 calculation to investigate the potential impact. This has found that changes to the hot water algorithms have the greatest impact.

The most significant changes introduced in SAP 10 as identified by BRE[90] are:

- Revised 'standard occupancy' heating pattern that assumes shorter hours of heating at weekends, with two heating periods instead of just one.
    - This reduces the mean internal temperature and hence the energy use by (5%-6%) in poorly insulated, homes with typical insulation (3% - 4%) and well-insulated homes (2% - 3%). This change will tend to reduce the systematic performance gap.
- Greater thermal bridging heat losses due to more pessimistic defaults
    - Leading to higher estimated energy use for space heating.
- Changes to the solid wall U-value calculation in RdSAP10.
    - About 18% of homes that previously had solid walls rated as U-value of 1.7 W/m²K will have U-values of 1.4 W/m²K or 1.1 W/m²K. This means average U-value of a solid wall is estimated to reduce from 1.7 W/m²K to 1.63 W/m²K. This will again reduce the systematic performance gap as a higher proportion of solid walled properties are poorly performing.
- Compulsory measurement of glazing in RdSAP10.
    - It is estimated that the difference in window area may be as high as 30% to 60% in some cases. This has been confirmed by the data from the forensic surveys where ten of the properties surveyed had total window area more than 30% different from the RdSAP default and in one case it was 61.8%. It is unclear how big an impact this change may have on the energy use, in addition the assumed U-value of glazing has changed and modern windows. In some cases, the U-value may get better but for modern windows the u-value will reduce.

There are other changes to SAP/RdSAP10 which may increase or decrease modelled energy use including:

- More characteristics of the hot water system considered

[90] RdSAP 2012 to RdSAP 10 upgrade: impact on ECO4 scoring, Prepared for: Ofgem,Date: 05.12.2023 Revision: 0.2 Status: Final - Commercial in Confidence, B R E G R O U P . C OM

    - Leading to higher estimated energy use for hot water (and therefore also higher heat gains from the hot water system) except where there is an electric instantaneous shower and no bath.
- The consideration of different types of low energy lighting
    - In particular LEDs, leading to lower heat gains from lighting as well as slightly lower energy costs.

There are also updated energy tariffs leading to lower EERs for properties with electric heating in particular.

The impact of the changes in SAP 10 on the energy efficiency rating and on the estimated energy use for space heating and hot water was assessed for the 'as 2021' version of the SAP assessment for the 45 properties that were subject to forensic surveys. In two cases the 'as surveyed' versions have been modelled as well to include the impact of improvements carried out since 2021.

Hot water

SAP 10 accounts for the number of baths and showers, the shower type (vented, vented plus pump, combi or unvented, electric instantaneous) and the shower flow rate (or kW capacity in the case of electric instantaneous). A six-minute shower is assumed. Where there is more than one type of shower in a property, equal use of each shower is assumed. Note that RdSAP 10 asks for total number of baths and showers, and the number of mixer showers.

Table 38 compares the modelled annual hot water heating energy use from SAP 10.2 with that from SAP 2012, showing the mean values obtained for the gas heated and electrically heated properties separately.

Table 38 comparison between modelled annual hot water heating energy use between SAP10.2 and SAP 2012.

Main heating fuel	Mean SAP10.2 – SAP2012 difference in hot water heating energy use (kWh/yr)	Percentage difference in hot water heating energy use compared to SAP2012
Gas	819.90	33.30%
Electricity	22.50	1.44%

In all but five cases there was an increase in estimated energy use for hot water in SAP 10 compared to SAP 2012.

The five cases with no increase in estimated energy use for hot water in SAP 10 were all properties with no bath and an instantaneous electric shower. These were broken down as shown in Table 39.

Table 39 Summary of cases with no increase in estimated energy use for hot water in SAP 10

Change in estimated hot water energy use	Number of properties	Details
More than 25% lower	2	These had combi boilers where the efficiency was taken from the SAP table rather than the PCDB. In SAP 2012 all the hot water will have been assumed to be from the combi boiler.
8.22% lower	1	With dual immersion as the main source of hot water. Again, the presence of the electric shower will have been ignored in SAP 2012.
No change	2	These had electric instantaneous hot water systems for all hot water, so these were accounted for in SAP 2012.

In all other cases there was an increase in estimated hot water use in SAP 10, and often this was significant as shown in Table 40.

Table 40 Summary of cases with an increase in estimated energy use for hot water in SAP 10.

Change in estimated hot water energy use	Number of properties	Details
Less than 5% higher	4	These all had an electric instantaneous shower but also had a bath.
Between 7.5% and 12.5% higher	6	These all had hot water from a hot water cylinder and one or more mixer showers. One had an electric immersion heater and no bath. All the others had regular gas boilers and a bath as well as the showers.
13.21% higher	1	Hot water from a hot water cylinder supplied by a heat pump (E9), with an electric instantaneous shower and no bath. This leads to an increase in the estimated hot water use as the instantaneous electric shower is less efficient than the heat pump

16.81% higher	1	This has a combi boiler with a bath but no showers.
Between 24% and 30% higher	3	These have combi boilers and a combination of mixer and electric instantaneous showers.
Between 32% and 35% higher	2	These have regular boilers and hot water cylinders with a pumped shower (12 l/min assumed flow rate).
Between 36% and 53% higher	25	These all have ‘combi or unvented’ mixer showers, with an assumed flow rate of 11 l/min, and all except two of them also have a bath (24 are combi boilers and one has a regular boiler with an unvented cylinder).

Space heating

In SAP 10, the estimated heat transfer coefficient (HTC) is generally very similar to that from SAP 2012 if a default y-value of 0.15 W/m2K is assumed. (The default y-value has been increased to 0.20 W/m2K in SAP 10 compared to 0.15 W/m2K in SAP 2012 but for all except the properties with new build EPCs, we have used thermal bridging details that give a y-value of 0.15 W/m2K in the model as this is the default in RdSAP 10). However, in some cases there is an increase in the space heating demand due to ventilation factors.

More generally the additional heat gains resulting from the increase in estimated hot water use (especially where there are combi boilers or pumped showers) and the shorter heating hours assumed at weekends lead to a lower estimated energy use for space heating, although offset slightly by the reduced heat gains from more efficient lighting.

Table 41 compares the modelled annual space heating energy use from SAP 10.2 with that from SAP 2012, showing the mean values obtained for the gas heated and electrically heated properties separately.

Table 41 Comparison of the modelled annual space heating energy use between SAP10.2 and SAP2012

Main heating fuel	Mean SAP10.2 – SAP2012 difference in space heating energy use (kWh/yr)	Percentage difference in space heating energy use compared to SAP2012
Gas	-267.37	-1.65%
Electricity	14.50	0.14%

Table 42 shows the breakdown of the numbers of properties in specified ranges of the change in estimated space heating energy uses:

Table 42 Summary of the number of properties in specified ranges of change in estimated space heating energy use.

Change in estimated space heating energy use	Number of properties	Details
More than 3% negative	12	All of these are between -3.00% and -4.00% except for one at -4.85% and one at -5.77%. None of these have electric instantaneous showers and all have a bath as well as one of more mixer shower.
Between -3.00% and -2.00% higher	15	Twenty-one of these are properties with gas boilers and mixer showers, although two have electric instantaneous showers and one has no showers, i.e. bath only.
Between -2.00% and 0.00% higher	8	These include two of the four electrically heated properties, plus two others which have electric instantaneous showers (and thus lower heat gains from hot water)
Between 0.00% and 2.25% higher	7	These include the other two electrically heated properties and all but one of the others has an

		electric instantaneous shower.
More than 3.50% higher	3	These are three of the four properties with new build EPCs.

One property (E9) was modelled with the heat pump that has been installed since 2021. In this case the heating energy use is estimated to be over 11% higher. There is a slight reduction in the efficiency of the heat pump so this appears to be primarily due to much lower heat gains from both hot water and lighting.

Energy efficiency rating (EER)

In most cases, the EER is lower in SAP 10 than in SAP 2012. In the case of electrically heated properties, the EER is over 20% lower due to the relatively high electricity tariff when SAP 10 was defined. However, for gas heated properties the difference is no more than -3.4% unless there is electric or solid fuel secondary heating and/or an electric instantaneous shower. In these cases the reduction in EER is primarily due to the higher estimated space heating and hot water use discussed above.

Table 43 Summary of the number of homes with different percentages of change in EER between SAP10 and SAP2012.

Change in EER	Number of properties	Details
Between -19% and -32% lower	4	These are the four electrically heated properties
Between -6.00% and	16	These properties all have secondary heating and/or an electric instantaneous shower.
-2.00% lower		Only three have gas secondary heaters and mixer showers.
Between -2.00% and 0.00% lower	23	These properties all have mixer showers as the only shower type. Most have no secondary heating but there are six with gas secondary heaters and three with an electric secondary heater.
Positive: 0.53% and 0.74% higher	2	

Comparison of full SAP 10.2 assessments with RdSAP 10

Following the introduction of RdSAP 10 on 15 June 2025, it is possible to compare the results from the modelling carried out in full SAP 10.2 with those from RdSAP 10.

We have only had time to look at a small sample of the forensic surveys, but the results do differ. In the case of electrically heated properties the energy efficiency ratings are very different (as expected) due to the retention of the same fuel tariffs from SAP 2012 in RdSAP 10 rather than the updated ones used in SAP 10.2.

A key issue identified by this exercise is the estimation of energy use for hot water. Appendix J of SAP 10.2 specifies shower flow rates of 11 l/min if from a combi or unvented system and 7 l/min if from a vented system. The RdSAP 10 software appears to use 7 l/min in all cases which has a significant effect on the results, giving lower hot water energy use (and higher energy efficiency ratings) for gas heated properties compared to those we obtained using SAP 10.2. At the time of writing, we are not sure if this is software error or if there is an omission from the RdSAP 10 specification. It is also unclear what should be assumed for the cold water temperature from Table J1, although this has less impact on the results.

There are also some other factors that are leading to slightly different results in RdSAP 10 compared to full SAP 10.2, including:

- Living area fraction – this is still based on the number of habitable rooms rather than the measured area. The RdSAP 10 specification states calculated fraction based on measured area can be used but software does not allow this, at least at present. In twelve of the forensic surveys the measured living area is more than 25% different from the RdSAP default based on number of habitable rooms, and in two cases this difference exceeds 100%. (However, as mentioned earlier, this has a relatively small effect on the estimated kWh per year).
- External doors - each door is always assumed to have an area of 1.85m2 which in many cases differs from the actual door area. (This also affects net external wall area).
- The simplifications for ‘rooms in the roof’ and the omission of small areas of sloping ceiling.

Specific issues with new build EPCs

Four of the properties surveyed had full SAP EPCs issued when they were built.

Although there were relatively few issues with these, three of the four had significantly incorrect thermal bridge details (clearly identifiable from the EPC input data before visiting the property). Also, two had incorrect U-values and two had incorrect ventilation details.

In one case a significant discrepancy arose from the very pessimistic default air permeability (15 m3/m2h@50Pa) that was able to be used for new build instead of carrying out a pressure test prior to 2022.

Note that in the case of the new build EPCs, the issues identified as 'assessor errors' (apart from the lengths of the applicable thermal bridges) may be due to incorrect information provided by the developer.

There was one property identified with a new build EPC that was an older, existing house, and it transpired that its EPC had been replaced by one for a house on a new development at the end of the road (same postcode) with very different characteristics. We identified this from on-line research and did not carry out a survey of this property.

Recommendations:

- Carry out checks of the input data for new build EPCs to confirm that the thermal bridging details are consistent with the built form.
- Require the OCDEAs check whether an existing EPC exists for an address (as required by DEAs) to avoid new build EPCs incorrectly replacing existing dwelling EPCs.

Specific issues with electrically heated homes

Four of the properties surveyed had electric heating.

One of these properties had an incorrect classification of storage heater type and incorrect electricity tariff. These resulted in an error of more than 60% in the energy efficiency rating.

In two others, electric storage heaters had been replaced by on-peak electric room heaters, resulting in much lower energy efficiency ratings (in one case by over 30%). In these cases, the energy use for space heating was also significantly reduced, so arguably the energy efficiency was improved but the running costs were higher due to the relatively high cost of on-peak electricity. This raises questions about the advice given on an EPC for properties with storage heaters.

In one of the above cases, the hot water system was also changed from immersion to instantaneous, which further reduced the estimated energy use and therefore offset the reduction in the EER to some extent.

In one case there were assessor errors regarding the controls for electric radiators (thermostats and programmers), but these seemed to have no effect on the SAP results.

Regarding SAP 10, as well as higher energy use the electrically heated properties come out with much lower energy efficiency ratings.

For the electrically heated properties, it is not the case that most changes make the EER better – mostly they make it worse.

Recommendations:

Clarify the advice provided on EPCs when there are heating or hot water systems using off-peak electricity tariffs.

Additional input data needed for the Home Energy Model (HEM)

On each of the forensic surveys, an attempt was also made to collect some of the additional information that may be needed for a “reduced data HEM”. Some general comments on our experience of this are as follows:

Some of this information is very straightforward to collate and could usually be obtained from the sketch plan and/or the photos required as evidence for RdSAP 10. These include:

Numbers of bedroom and bathrooms
Property dimensions, including area of living room
Details of windows and doors, including any shutters
Location of heating system
Presence of immersion heater
Number of sheltered sides/general shelter
Presence of heritage/conservation considerations

It was also straightforward to collect the width, height and type of each radiator, although this did add a little bit of time to each survey, and details of cooking appliances.

The following were more problematical but often possible:

Electricity tariff (by asking the occupant)
Window reveal depth (for shading), where consistent for all openings
Heating flow temperature
A photo of the consumer unit to show its state and the capacity of the isolator and the main fuse
Lengths of hot water distribution pipework (approximate estimates based on locations of boiler/hot water cylinder and distances to the kitchen and bathroom(s) from the room dimensions).

We were generally not able to obtain the following:

Depth of overhangs (to glass) and distance shading (we took photos away from the properties, but guidance would be needed on how to assess this)
Flow rates of showers
Energy ratings of appliances

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