# Deconstruct: a scalable method of as-built heat power loss coefficient inference for UK dwellings using smart meter data

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**Abstract**

Dwellings in the UK account for about 25% of global energy demand, of which 60% is space heating making this a key area for efficiency improvement. Dwelling UK Energy Performance Certificates (EPC) are currently based on surveyed data, rather than energy use monitoring. The installation of smart meters provides an opportunity to develop an EPC based on in situ dwelling thermal performance.

This paper presents 'Deconstruct' – a method of estimating the as-built Heat Power Loss Coefficient (HPLC) of occupied dwellings as a measure of thermal performance, using just smart-meter and meteorological data. Deconstruct is a steady-state grey box building model combined with a data processing pipeline and a model fitting method that limits the effects of confounding factors. Smart meter data from 780 UK dwellings from the UK Energy Demand Research Project (EDRP), was used to calculate a median HPLC of 0.28 kW/˚C (±15%). The stability of the estimate across multiple years of data with different weather and energy use was demonstrated. Deconstruct was found to be suitable for large scale inference of dwelling thermal properties using the UK's new smart metering data infrastructure.

**Keywords**
Energy demand, residential sector, smart meter, building assessment methods, building energy models

**Nomenclature**

| Symbol | Description | Unit |
|---|---|---|
| $c_p$ | Specific heat capacity of air | J/kg K |
| $\rho_{air}$ | Density of air | kg/m$^3$ |
| $A_{sol}$ | Effective solar aperture | m$^2$ |
| $F_T$ | Change of $T_{in}$ with change in $T_{ex}$ | - |
| $Q_{ve}$ | Air change rate coefficient | m$^3$/s |
| $H_{tr}$ | Transmission heat transfer coefficient | kW/˚C |
| HPLC | Heat Power Loss Coefficient | kW/˚C |
| HTC | Heat Transfer Coefficient | kW/˚C |
| $I_{sol}$ | Solar irradiance | kW/m$^2$ |
| $P_B$ | Measured base-load power demand | kW |
| $P_H$ | Measured power use for heating | kW |
| $P_{H,D}$ | Power demand for heating | kW |
| $P_{elec}$ | Measured electrical energy demand | kW |
| $P_{gas}$ | Measured gas energy demand | kW |
| $P_{tot}$ | Total measured energy demand | kW |
| $T_{ex}$ | External air temperature (2m from surface) | ˚C |
| $T_{fix}$ | Reference external air temperature for Tin model | ˚C |
| $T_h$ | Base-load to heating regime change point | ˚C |
| $T_{in}$ | Dwelling mean internal temperature | ˚C |
| $T_0$ | $T_{in}$ at $T_{fix}$ | ˚C |
| $\eta_B$ | Base-load utilisation factor | - |
| $\eta_{HS}$ | Heating system efficiency | - |
| $\Phi_B$ | Heat gain from base-load | kW |
| $\Phi_O$ | Metabolic heat gains from occupants | kW |
| $\Phi_{HS}$ | Heat flow rate from heating system | kW |
| $\Phi_{sol}$ | Whole dwelling heat flow rate from solar gains | kW |
| $\Phi_{tot}$ | Total heat flow rate | kW |
| $\Phi_{tr}$ | Total conductive heat transfer | kW/˚C |
| $\sigma$ | Standard error | - |
| CVRMSE | Coefficient of Variance of Root Mean Square Error | % |

# 1 INTRODUCTION

The domestic sector in the UK accounts for 25% of energy demand [1,2], while space heating accounts for almost 60% of this total [1], making it a key area for efficiency improvements. Meanwhile, trends in energy use reduction in homes do not appear on track to meet UK climate targets [3], while flagship policies for improving efficiency such as the Green Deal have not been successful [4].

Roels [5] and Yilmaz et al. [6] highlighted that there is a lack of established methods for estimating the as-built thermal performance of dwellings in the UK in a manner which can be cost-effectively scaled to large numbers of dwellings. The Energy Performance Certificate (EPC) [7] is currently the most widespread assessment and delivers normalised energy demand estimates based on building characteristics derived from an on-site inspection. This approach has come under extensive criticism [2,8–16]. Most notably, the on-site inspection is costly (£60-120) [17], intrusive, and subjective, resulting in significant variation in delivered certificates depending on the inspector [18], limiting its application to situations where regulation has made it compulsory. It furthermore relies on assumptions for many key values, limiting its ability to deliver as-built thermal performance. The EPC is frequently incorrectly interpreted as reporting real as-built consumption, rather than a normalised value based on assumed construction.

There are many challenges to obtaining reliable performance estimates for dwellings, and as a result there are widespread observations of a 'performance gap' between expected and measured total energy demand [19–21]. This has been taken by some as evidence for the rebound effect [22,23], but is likely better described as a 'credibility gap' [24,25] caused by limitations of the assessment methods. Alternative approaches to in-situ measurement of dwelling thermal performance have been presented in [26–32].

The installation of smart meters in UK dwellings that collect and transmit energy readings in real time enable new approaches to energy demand modelling thanks to the data they provide [33,34]. The aim of the research presented in this paper is to develop a method to characterise "as-built" thermal performance of individual UK dwellings with respect to heating, independently of occupant thermal behaviours, that can be performed rapidly and non-intrusively at scale, using smart meter data collected from large numbers of dwellings.

To achieve this aim, the newly developed 'Deconstruct' method is presented, which is the name given to the combination of a grey-box physical model linking metered energy demand to the building thermal balance and internal temperature, and a data sampling method and model-fitting algorithm to infer thermal and temperature model parameters. Deconstruct can infer several physical variables separately from occupant-driven ones by using known building physics to describe the relation between weather conditions and power demand. This work focuses on the estimation of the whole building Heating Power Loss Coefficient (HPLC), which combines the fabric Heat Transfer Coefficient (HTC) with the space heating system efficiency $\eta_{HS}$ and enables the characterisation of heating performance of dwellings.

The method aims to be scalable in that it may readily be applied to large numbers of dwellings without incurring significant manual effort, costs, or being computationally prohibitive. Minimising the need for manual intervention implies that the approach should be robust with respect to data quality and the effects of confounding factors, such as occupants. This motivates the use of a grey-box model avoiding the need for internal dwelling measurements beyond the smart meter.

# 2 THEORY

This section defines the **Heating Power Loss Coefficient** (HPLC) in terms of metered power demand using a steady-state grey-box model of the heating and base load demand and relates it to the Heat Transfer Coefficient (HTC), which can be measured by a co-heating test. The dwelling steady state net heat flow rate $\Phi_{tot}$ (kW) is defined using established formulations of dwelling heat transfer processes, calculating the thermal balance as the sum of contributions to heat flow in/out of the dwelling. A model of dwelling internal temperature is also defined. Linking functions are defined describing the dependence of metered energy demand $P_{tot}$ (kW) on the thermal balance.

## 2.1 Heat Transfer Coefficient

The Heat Transfer Coefficient (HTC) (kW/°C) of a dwelling is an indicator of overall steady-state dwelling fabric thermal performance. It has been defined in co-heating tests as the absolute change in quasi-steady-state dwelling heat flow with change in temperature difference between the internal and external environments, controlling for solar gains [32,35–37], as shown in eq. 1 where $\Delta T = T_{ex} - T_{in}$. Co-heating tests produce an accurate measurement of whole-building performance by carefully monitoring the energy necessary to maintain an unoccupied building at a set internal temperature, controlling for solar gain, over a period of several days to several weeks [35].

$$HTC = \frac{d(\Phi_{tr} + \Phi_{ve})}{d\Delta T} = H_{tr} + \frac{d\Phi_{ve}}{d\Delta T} \qquad (1)$$

The dwelling net heat flow $\Phi_{tot}$ is given by eq. 2 in terms of the fabric transmission losses, ventilation losses, solar gains, and base-load gains.

$$\Phi_{tot} = \Phi_{tr} + \Phi_{ve} + \Phi_{sol} + \Phi_B + \Phi_O \qquad (2)$$

The fabric heat transfer $\Phi_{tr}$ is given by eq. 3 as a function of whole dwelling heat transfer coefficient $H_{tr}$ and the internal-external temperature difference following [35]. $H_{tr}$ combines direct heat transfer from internal conditioned space across the fabric to the external environment, as well as heat flows to the ground, to unconditioned spaces, and to adjoining buildings, and assumes that there is a single thermal zone and that the effect of ground temperature difference is negligible.

$$\Phi_{tr} = H_{tr}(T_{ex} - T_{in}) \qquad (3)$$

Linearisations of total solar gains $\Phi_{sol}$ as a function of irradiance $I_{sol}$ (eq. 4) and ventilation heat loss $\Phi_{ve}$ (eq. 5) are used, based on co-heating test methods [36,37]. In these equations, $A_{sol}$ is the effective solar aperture (equivalent surface area of building which absorbs solar energy) and $Q_{ve}$ is the effective volumetric air flow rate constant for the dwelling. Values $c_p$ and $\rho_{air}$ are the specific heat capacity and density of air.

$$\Phi_{sol} = A_{sol} I_{sol} \qquad (4)$$

$$\Phi_{ve} = c_p \rho_{air} Q_{ve}(T_{ex} - T_{in}) \qquad (5)$$

The thermal gains $\Phi_B$ from energy used in lighting, appliances, plug loads, and water heating are captured in the base-load parameter $P_B$. We introduce a parameter $\eta_B$, where $0 \leq \eta_B \leq 1$, describing the fraction of base-load power that contributes to the net internal thermal gains (eq. 6).

$$\Phi_B = \eta_B P_B \qquad (6)$$

Metabolic gains from occupants $\Phi_O$ can contribute moderately to dwelling energy balance, as these are of the order of 0.06kW per occupant [7] while metered baseload power is of the order of 0.5kW (see Section 5) and heating system power of the order of several kW. These are not considered in the definition of the HTC as co-heating tests are performed on unoccupied dwellings, but should be included for the occupied dwelling heat balance. Occupant thermal gains are not considered to be seasonally dependant in building standards [7].

Heating power $P_{H,D}$ equal to the net losses $\Phi_{tot}$ is needed when the net heat flow is negative ($\Phi_{tot} < 0$). The heating system power $P_H$ required to meet the heating demand power $P_{H,D}$ is a function of the mean heating system efficiency $\eta_{HS}$ (eq. 7).

$$P_H = \frac{P_{H,D}}{\eta_{HS}} \qquad (7)$$

The total dwelling metered power demand $P_{tot}$ can therefore be modelled using the piecewise function eq. 8. Outside of the heating regime $P_{tot} = P_B$.

$$P_{tot} = \begin{cases} 1/\eta_{HS}\,|\Phi_{tot}| + P_B \text{ if } \Phi_{tot} < 0 \\ P_B \text{ otherwise} \end{cases} \qquad (8)$$

HTC can be expressed in terms of total metered power demand $P_{tot}$ instead of heat flow $\Phi_{tot}$. Analysis conducted in [38] determined that base-load power demand is not temperature dependent implying that $d\Phi_B/d\Delta T = 0$, while occupant gains $\Phi_O$ can also be assumed not to be correlated with temperature so $d\Phi_O/d\Delta T = 0$. Therefore, the change in power demand with change in temperature can be simplified and the definition of HTC (eq. 1) substituted to derive eq. 9.

$$\frac{dP_{tot}}{d\Delta T} = |\frac{d(\Phi_{tr} + \Phi_{ve})}{d\Delta T}| = 1/\eta_{HS}\,(H_{tr} + \frac{d\Phi_{ve}}{d\Delta T}) = 1/\eta_{HS}\,HTC \qquad (9)$$

As $\Phi_{tot} < 0$, $|\Phi_{tot}| = -\Phi_{tot}$, total power is therefore given by eq. 10.

$$P_{tot} = \frac{1}{\eta_{HS}}(HTC(T_{in} - T_{ex}) - A_{sol}I_{sol} - \eta_B P_B - \Phi_O) + P_B \qquad (10)$$

## 2.2 Heating Power Loss Coefficient

Inspection of eq. 10 indicates that it is not possible to separate HTC and $\eta_{HS}$ without additional information as these parameters are covariant with respect to ΔT. A **Heating Power Loss Coefficient** (HPLC) is therefore defined which incorporates thermal losses from the fabric and the heating system (eq. 11).

$$HPLC = HTC/\eta_{HS} \qquad (11)$$

Substituting eq. 11 into eq. 10 gives the total power demand during the heating regime (eq. 12).

$$P_{tot} = HPLC(T_{in} - T_{ex}) - \frac{1}{\eta_{HS}} A_{sol} I_{sol} - \frac{\eta_B}{\eta_{HS}} P_B - \frac{\Phi_O}{\eta_{HS}} + P_B \qquad (12)$$

As eq. 12 depends on the internal temperature and this is not widely monitored, it was necessary to define a model of internal temperature, which is described in Section 2.3. Incorporating a linear internal temperature model (eq. 15) gives a linear expression for $P_{tot}$ during the heating regime (eq. 13), taking into account the internal temperature coefficient $F_T$.

$$\begin{aligned} P_{tot} = - \quad & HPLC((1 - F_T)T_{ex} - T_0 + F_T T_{fix}) \\ & - A_{sol}/\eta_{HS}\, I_{sol} - \eta_B/\eta_{HS}\, P_B - \frac{\Phi_O}{\eta_{HS}} + P_B \end{aligned} \qquad (13)$$

We can therefore calculate the HPLC, which characterises energy loss from the dwelling fabric and heating system, using the derivative of metered $P_{tot}$ with respect to external temperature (eq. 14). This implies that it is possible to infer the HPLC using only remotely collected smart meter and climate data. A robust approach to performing this inference is described in Section 3.

$$\frac{dP_{tot}}{dT_{ex}} = -HPLC(1 - F_T) \qquad (14)$$

## 2.3 Internal temperature model

Internal temperatures were modelled in order to address the lack of measurements by using a linear dependence on external temperature. This is defined in eq. 15 where $F_T$ is a factor describing the dimensionless change of $T_{in}$ (˚C) with $T_{ex}$ (˚C) (i.e. $\frac{dT_{in}}{dT_{ex}}$) and $T_0$ (˚C) is the mean internal temperature at external temperature $T_{fix}$ = 5˚C, which is chosen in order to facilitate comparison with existing work in this field including [39], [40], and [41].

$$T_{in} = F_T(T_{ex} - T_{fix}) + T_0 \qquad (15)$$

Reference [42] presents evidence that a linear model is appropriate when heating schedules are constant, while [40] considers also quadratic terms. In [38], the linear model fit to measured temperature data was compared to higher order (polynomial) formulations. It was found that the polynomial coefficients were not statistically significant and that the linear model was a reasonable approximation to measured temperature data. Reference [43] found through clustering of indoor temperature profiles that the majority of dwellings adopted one of four typical patterns, with relatively little difference between weekdays and weekends, supporting the simplifying assumption that heating schedules are roughly constant.

Parameter $F_T$ is set in this work as an average value as a first order approximation, making it possible to infer HPLC in the absence of measured internal temperature data. $T_0$ is estimated on a per-site basis.

# 3 METHOD

Deconstruct enables the inference of $HPLC$, $P_B$, $T_0$, and $A_{sol}$; we focus in this paper on the $HPLC$ as a measure of dwelling thermal performance with respect to heating. This parameter incorporates the transmission, ventilation, and heating system losses of the dwelling, thereby covering key physical determinants of dwelling heating demand i.e. HPLC is an indicator of how energy efficient a house is at providing space heating. In order to infer dwelling parameters from metered energy demand data, a 'post-hoc control trial' methodology was developed, which makes use of a structured sampling of accumulated smart meter data to produce robust parameter estimates. This approach takes advantage of the simplicity and low cost associated with accumulating smart meter data over a long period. During this collection period, natural variability in weather and power demand will result in a subset of days during which conditions are optimal for inferring dwelling parameters using the simplified thermal model. Suitable filters were defined to avoid over-fitting of data by limiting the assumptions made for filtering.

One full year was used of daily average data including total metered energy, external temperature, and solar irradiance for a dwelling. Daily average data was deemed to be suitable for steady state approximation based on previous findings. [44] found that although work on co-heating in [36] found that 3-day averages were needed to achieve a steady thermal state in a co-heating test, when considering metered data the additional variance under real-world use conditions resulted in there being effectively no change in results between 1-day and 3-day averages, while the reduction in dataset size caused the uncertainties in the inferred model coefficients to increase substantially.

Total power was calculated as the sum of metered electricity $P_{elec}$ and gas $P_{gas}$, thus accounting for all heat sources including secondary heating (which applies to many dwellings [45]), in which case the HPLC will encompass the combined losses from the various heating systems. Dwellings were required to have no more than 50% missing daily values. Significant un-metered heating energy (e.g. wood, coal or oil burning) could not be accounted for but is not common in the UK where homes have both gas and electricity.

Parameters $F_T$ and $\eta_B$ must be set independently before it is possible to infer $HPLC$. In the absence of internal temperature monitoring, $F_T$ may be set to a common value for all dwellings under analysis (for example a nationally representative value). An approach to determining a value for $F_T$ is presented in Section 3.3.1.

The values of $\eta_B$ and heating system efficiency $\eta_{HS}$ do not affect the inference of HPLC. As $\eta_B P_B$ is assumed to be constant it will not affect the change in energy demand with temperature, while $\eta_{HS}$ is integrated in the definition of HPLC and therefore there is no need to make an assumption for its value when estimating HPLC. For the purposes of the parameter inference, the base-load gain parameter $\eta_B$ was set to 1 as a simplifying assumption made on the basis that most energy transferred into a dwelling will eventually be dissipated as heat. Further study could be made to establish a more realistic value for this parameter, this would not affect the inferred HPLC results.

The base-load $P_B$ is estimated from a dwelling data sample selected using the filters described in Section 3.2, which are designed to select non-heating days.

The $HPLC$ is inferred following the approach in Section 3.3.2 using as input a low solar gain subsample of the data selected using the filtering approach described in Section 3.3 and the base-load power $P_B$. $T_0$ and $A_{sol}$ may be inferred as shown in Table 1, but this is not discussed in the scope of this paper. A summary of the model inputs and outputs and the source of each parameter (input data or model inference) can be found in Table 1, while a summary of the steps is shown in Figure 1.

**Table 1: Summary of model parameters and source of parameter value.**

| Symbol | Description | Source | Unit |
|---|---|---|---|
| $A_{sol}$ | Effective solar aperture | Estimated from low temperature sample | m$^2$ |
| $I_{sol}$ | Solar irradiance | Gridded weather data, using site location | kW/m$^2$ |
| $HPLC$ | Fabric and heating system loss rate | Estimated from low solar gain sample | kW/˚C |
| $P_B$ | Base-load power appliances, lighting hot water, and plug loads | Estimated from high solar gain sample | kW |
| $P_{tot}$ | Total measured dwelling power demand | Sum of electricity and gas smart meter power $P_{elec}$ and $P_{gas}$ | kW |
| $T_{ex}$ | Ambient external air temperature | Gridded weather data, using site location | ˚C |
| $T_{fix}$ | External reference temperature | Set to 5˚C | ˚C |
| $T_0$ | Internal temperature when the external temperature equals $T_{fix}$ | Estimated from low solar gain sample | ˚C |
| $F_T$ | Slope of internal against external temperature | Set using national data or $T_{in}$ data | - |
| $\eta_B$ | Fraction of base-load contribution to dwelling thermal balance | Set to 1 for simplifying assumption | - |
| $\eta_{HS}$ | Heating system efficiency | Set from dwelling metadata, ignored if only HPLC is needed | - |

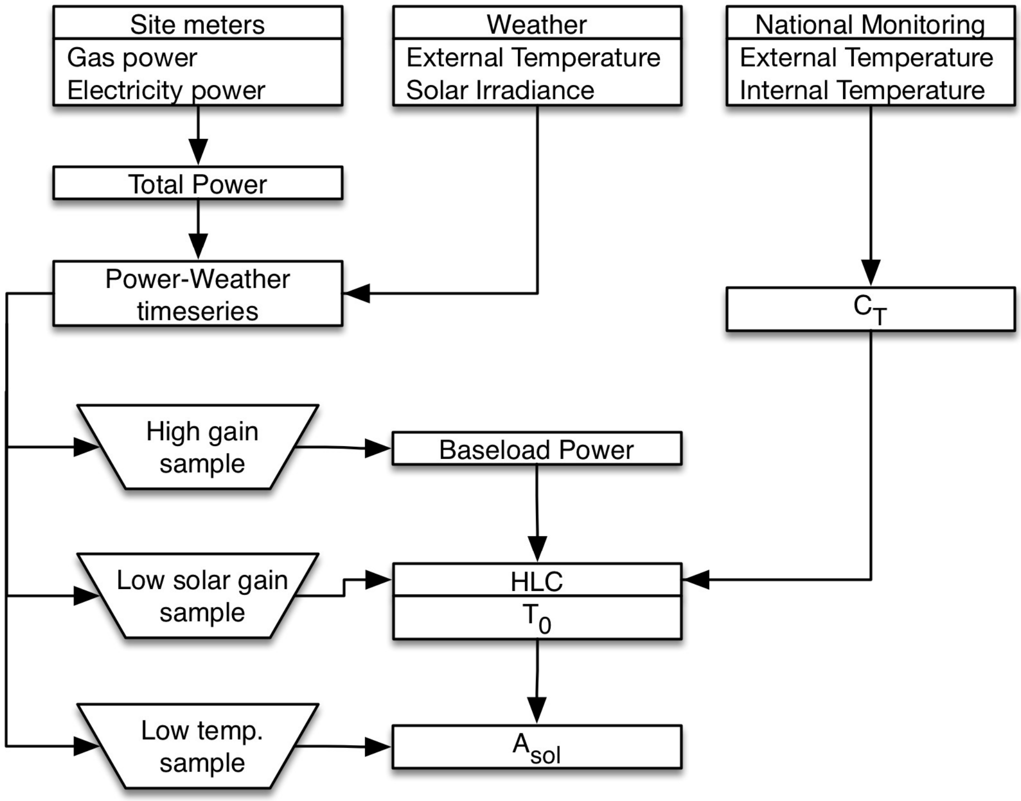


**Figure 1: Overview of Deconstruct method inputs and steps for parameter estimates. Arrows denote the dependence of output data or coefficients on inputs. For example, the calculation of $A_{sol}$ requires the low temperature sample and the values for coefficients $HPLC$ and $T_0$.**

## 3.1 Data filters

This section describes the data filters, required to prepare the input data and derive the sub-samples described shown in Figure 1 and Table 1.

### 3.1.1 Error filter

Rows where gas, electric, or total power were zero or missing were removed.

### 3.1.2 Outlier removal

Existing literature determined that the modified Z-score approach is suitable for outlier identification and removal in energy data [46–48]. This calculates an outlier metric based on dataset medians instead of means, making the filter more robust to highly skewed distributions. It is important that the outlier filter is applied only after filtering for errors because these values can affect the median calculation and result in incorrect identification of outliers.

### 3.1.3 Absence filter

To remove days where the building appeared to be unoccupied, it was assumed that heating demand should increase monotonically as external temperature decreased for a dwelling with a normally operating heating system. A filter was applied which selected a power cut-off value defined as follows. The power demand $P_{Tmax}$ for the highest temperature data point in the sample was used as a lower cut-off threshold for the power value, removing all points where $P_{tot} < P_{Tmax}$ (Figure 2). As the occupancy state is effectively inferred from the energy demand, dwellings which are occupied but not heated will appear identical to unoccupied dwellings.

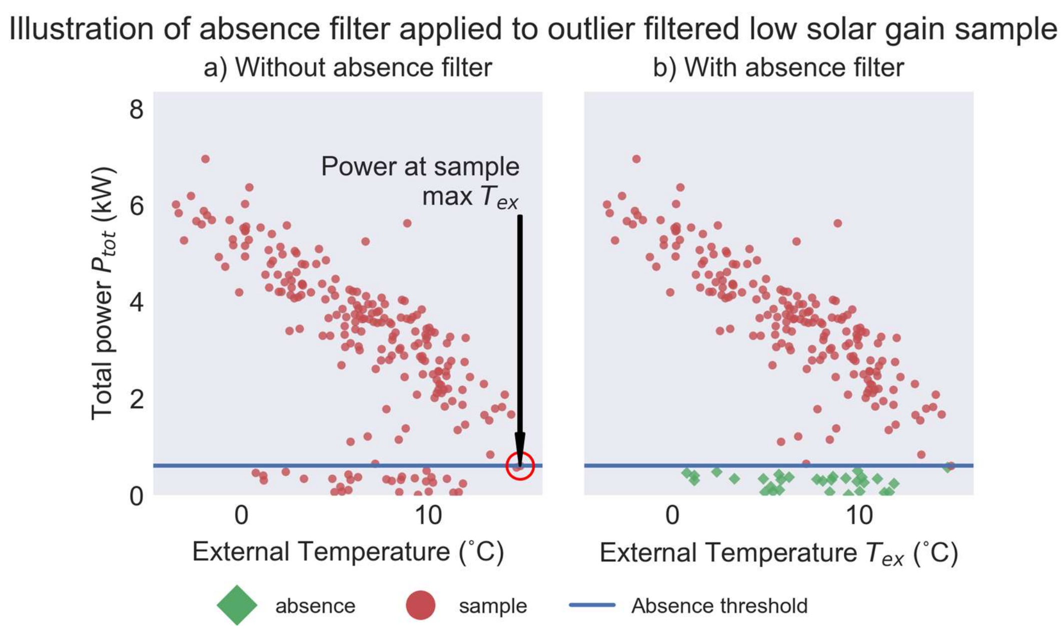


**Figure 2: Illustration of absence threshold filter applied to a low-solar gain sample with errors and outliers removed. a) shows the input sample with the power demand $P_{Tmax}$ for the highest temperature data point in the sample highlighted (red circle and annotation). b) demonstrates the effect of the absence filter by showing the resulting output sample and the removed data points.**

## 3.2 Base-load power sample

Base-load power is defined as the mean power outside of the heating regime, where power is independent of weather conditions and normally distributed about the mean [38]. The sample requires high solar gains and a minimum temperature cut-off such that heating is not expected to operate during the selected days. The filters applied are:

1. Missing values and error removal filter (Section 3.1.1)

2. High temperature filter, $T_{ex} > 18^{\circ}C$. This value was chosen such as to be higher than the heating base temperature of the majority of buildings [49], while retaining sufficient data in the summer months.

3. High solar gains filter, $I_{sol} > 0.1kW/m^2$. This threshold was set empirically to eliminate unusual conditions (high temperature with extremely low solar gains).

4. Modified z-score outlier removal filter (Section 3.1.2)

Base-load power $P_B$ is the mean of the resulting sample.

## 3.3 Low solar gain sample

A data sample selection with low solar gain is suitable for estimating HPLC and internal temperature model parameters. Limiting solar gains greatly simplifies the model since solar gains introduce complex time-of-day, time-of-year, and building geometry factors into the energy model. Using the low solar gain condition, eq. 13 may be simplified to eq. 16:

$$P_{tot} = -HPLC(1 - F_T)T_{ex} + HPLC\ T_0 - HPLC\ F_T T_{fix} + P_B(1 - \eta_B/\eta_{HS}) - \Phi_0/\eta_{HS} \qquad (16)$$

To obtain a low solar gain sample the following filter strategy was applied:

1. Error filter. This filter removes points with missing data, see Section 3.1.1.

2. Low solar irradiance filter. This filter selects days where the mean solar irradiance is below a given cut-off value of 0.05kW/m$^2$. Solar gains can contribute significantly to a dwelling's energy balance and bias the result. This filter is based on work by [36,50,51] and is particularly effective in the UK because the weather is often cloudy.

3. Outlier removal filter, according to Section 3.1.2.

4. Temperature backstop filter to eliminate days where $T_{ex}$ is greater than a cut-off temperature. The upper temperature cut-off is set to 15˚C following work by [40,52–54] which showed a statistically better fit to consumption data below 15°C.

5. Absence filter, see Section 3.1.3.

The application of these filters is illustrated using a single site in Figure 3, demonstrating that the solar gains filter has the largest effect. It is critical that the outlier filter be applied only *after* the desired subset of data has been selected through the low solar gain filter in order to ensure that the outlier filter does not mark points in the heating regime as outliers relative to the median power demand.

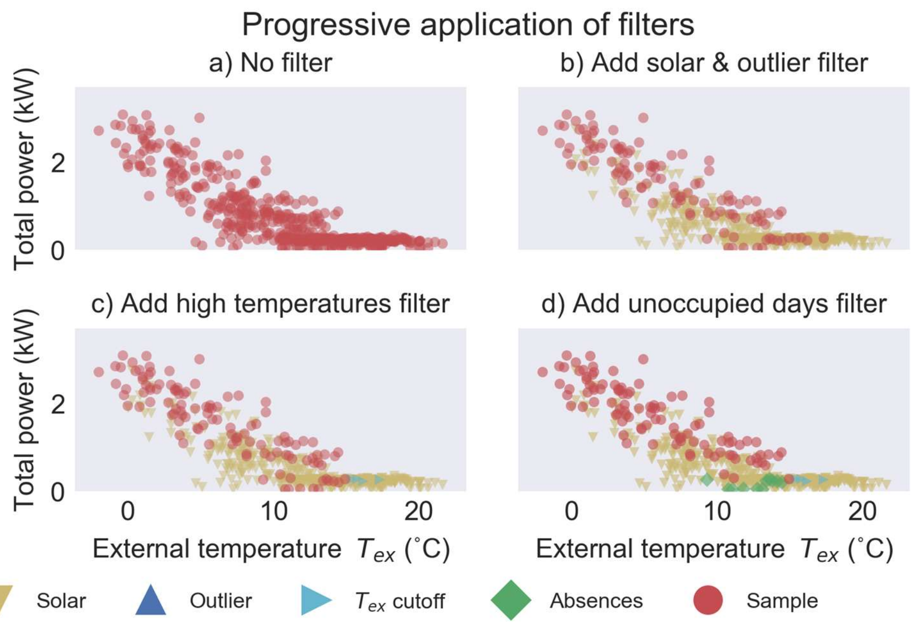


**Figure 3: Illustration of the effects of adding each filter in turn to the data from an example dwelling. a) Data with no filtering. b) Sample after application of the low solar gain filter and outlier removal. c) Filter for external temperatures above a 15˚C cut-off. d) Filter for unoccupied days.**

### 3.3.1 $F_T$ estimate

For dwellings without $T_{in}$ measurements, factor $F_T$ is set using the nationally representative Energy Follow Up Survey (EFUS) dataset (described in the Section 4.2), calculated using the linear regression of internal against external temperature for a low solar gain sample as described in Section 3.3.

### 3.3.2 HPLC estimate

The HPLC is estimated using the gradient of the power demand in the lower solar gain sample (eq. 16) with respect to external temperature (eq. 14).

## 4 DATASETS

The Deconstruct method requires daily total energy readings, linked to temperature and solar irradiance. Energy data was drawn from the Energy Demand Research Project (EDRP) smart meter readings, provided by EDF Energy (EDRP-EDF). This was associated with weather data from the UK

MetOffice, as weather monitoring was not performed concurrently with energy metering. Dwelling internal temperature monitoring was obtained from the nationally representative Energy Follow-Up Survey (EFUS) and linked to weather data. Energy data from EFUS was not used as it does not contain daily gas meter data.

## 4.1 EDRP-EDF data

The Energy Demand Research Project (EDRP) was a major project from 2007 to 2010 implemented by 4 major energy suppliers to test smart metering infrastructure and measure customer response to energy feedback [55]. The UCL Energy Institute partnered with EDF UK to obtain dwelling energy meter and metadata for 1,879 dwellings in London and Southeast England from these trails, 780 of which included both electricity and gas readings necessary for the Deconstruct method. The dwelling metadata included a partial postcode, which was used to geo-reference the dwelling and allowing it to be associated with weather data (see supplementary material).

## 4.2 EFUS data

This research used monitored temperature data from a sample of 823 dwellings from the 2011 EFUS to estimate values for $F_T$. Temperatures were monitored at 20-minute intervals in three zones within the dwelling (living room, hallway, and main bedrooms) for approximately one year [56]. Temperatures were resampled to daily averages, removing points where indoor temperatures were below 0˚C or above 40˚C, and a dwelling mean temperature was calculated. The Government Office Region (GOR) geographical identifier was used to link dwelling monitoring data with external temperature and solar irradiance from the MetOffice. Weightings for each site were provided to enable nationally representative distributions to be generated.

## 4.3 Weather data

Temperature and solar irradiance data were obtained from the UK MetOffice Numerical Weather Prediction (NWP) model gridded dataset with spatial resolution ~0.036˚ covering the British Isles [57]. The Metoffice described NWP data as being more accurate at high resolutions than interpolated weather station data, as it incorporated far more data sources (e.g. satellite data).

## 5 RESULTS

The EFUS dataset was used to determine a value for $F_T$ for the UK. HPLC estimates were then made for the dwellings in the EDRP-EDF dataset using this value. HPLC uncertainties were estimated using a Monte-Carlo simulation approach.

### 5.1 Internal temperature model

A representative value of $F_T$ for England was estimated using English Follow Up Survey (EFUS) data. The irradiance data associated with EFUS dwellings was used to produce site data subsets under low solar gain conditions matching those used for estimating HPLC. $F_T$ was estimated for each EFUS site as the slope of a linear regression of the internal temperature against external temperature. Values of $F_T$ with standard error greater than 30% were filtered on the basis that the model was not meaningfully calibrated in those cases; the resulting distribution is shown in Figure 4. EFUS provided per-site weightings which can be used to calculate nationally representative statistics using the buildings sampled. A nationally representative value $F_T = 0.17$ was calculated as the weighted mean of the retained results.

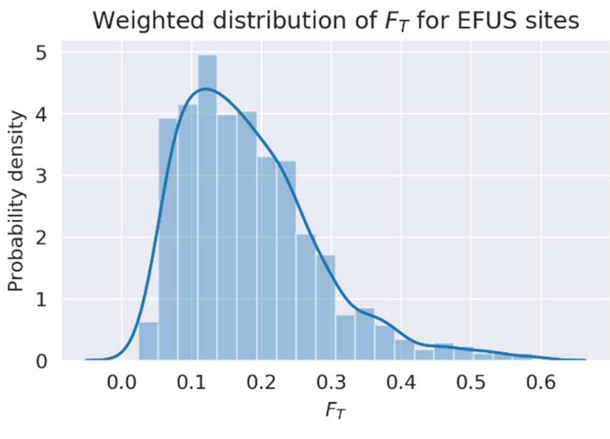


**Figure 4: Distribution of $F_T$ for EFUS dwellings weighted by EHS-provided sample weights to obtain nationally representative distribution, filtered to remove cases where standard error was >30%.**

### 5.2 HPLC estimates

Of 780 dwellings in the EDRP-EDF dataset having both gas and electricity data, 654 met the data quantity and quality requirements (the significant reduction in number due to poor data quality is a common problem with energy data not collected under controlled conditions). The 654 dwellings had a total of 361,761 days of data, an average of 654 days of data per site. Of these, dwellings 541 achieved acceptable model calibration according to recommendations from ASHRAE for steady state model calibration [58], i.e. the model Coefficient of Variance of Root Mean Square Error (CVRMSE) was under 30%. The excluded sites can be considered to be inadequately modelled using this method. This implies that a fraction of the building stock cannot be assessed using Deconstruct, nevertheless it is possible to reliably determine which dwellings this method cannot be applied to.

The resulting distribution of HPLC values across all sites is shown in Figure 5 with descriptive statistics in Table 2, a median HPLC of 0.28±0.04 kW/˚C (see uncertainty calculation in Section 5.2.1) was found.

The EDRP-EDF HPLC results may be compared with the dwelling heat loss values calculated by the Cambridge Housing Model (CHM), which based on an extensive building survey and a modified SAP calculation [59]. The CHM reports the HTC (“Dwelling Heat Loss”) and the heating system efficiency. This HTC was based on the combined heat transfer properties of the building elements (walls, windows, roof, etc) inventoried by the building survey, as well as the assumed ventilation losses, while the heating system efficiency was derived from the SAP tables for the building heating system. The HPLC values for the CHM buildings equipped with gas or electric heating were calculated according to eq. 11, summary statistics are presented in Table 2 and Figure 5. There is a good match between the HPLC distribution and the nationally representative CHM values with a 6% deviation in the mean. The CHM distribution includes a higher diversity of buildings, which may be reflected in the slightly higher proportion of larger CHM HPLC values.

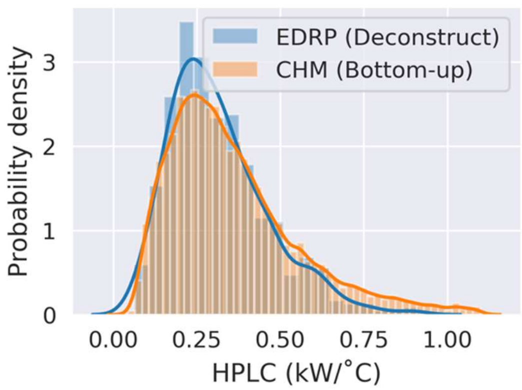


**Figure 5: Distribution of HPLC estimates for 541 EDRP-EDF dwellings where collected data quality was sufficient to produce an HPLC estimate compared to HLPC values calculated bottom-up from the Cambridge Housing Model (CHM)**

**Table 2: Descriptive statistics of the HPLC estimates for the EDRP-EDF data (inferred using Deconstruct) and the CHM data (calculated bottom-up).**

| | 25% percentile | 50% percentile | 75% percentile | Mean |
|---|---|---|---|---|
| EDRP-EDF HPLC (kW/˚C) | 0.21 | 0.28 | 0.39 | 0.31 |
| CHM HPLC (kW/˚C) | 0.20 | 0.29 | 0.41 | 0.33 |

Figure 6 shows the power and HPLC grouped by dwelling type for the EDRP-EDF and CHM. The pattern of relative magnitudes of power and HPLC across dwellings types is similar, as the heat loss is a major driver of total power demand. Flats and terraced houses tend to be more efficient than detached houses due to differences in ratio of exposed surface area to dwelling volume and their smaller size as HPLC is not normalised by floor area.

Overall, the good agreement between inferred and bottom-up HPLC values indicates that Deconstruct produces a reasonable estimate of the HPLC. Further work is needed to investigate the differences between the two estimates. As the EDRP-EDF sample is not nationally representative unlike the CHM, part of the deviations stem from the greater diversity of dwellings in the CHM, while part will be related to the difference between assumed and real building characteristics.

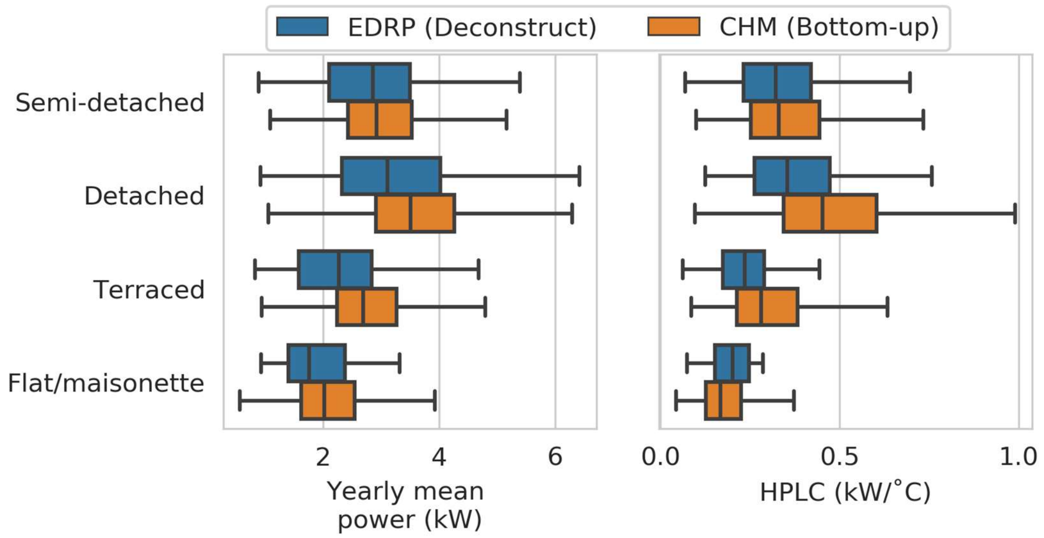


**Figure 6: Comparison of mean yearly power demand and HPLC for EDRP-EDF (inferred using Deconstruct), as well as the power and HPLC from CHM (bottom-up calculation), as a function of dwelling type.**

$T_0$ was estimated in addition to HPLC, however the uncertainties in this parameter were large - on average 2˚C relative to typical mean internal temperatures in ranges of 15-25˚C. Furthermore, it was found that $T_0$ was particularly sensitive to the assumption made for the base load gains $\eta_B$. The mean difference in $T_0$ estimate between setting $\eta_B = 0$ and $\eta_B = 1$ was 3˚C but could be as large as 10˚C. This result indicated that further development is needed in order to produce reliable $T_0$ estimates.

### 5.2.1 Uncertainty

Two approaches were used to estimated HPLC uncertainty. A Monte Carlo (MC) approach described by the Joint Commission for Guides in Metrology (JCGM) [61] was used to propagate uncertainty using known input uncertainty distributions to numerically estimate the output uncertainty distribution. The input distributions are described in Table 3, the uncertainty in electricity metering is assumed to be negligible. This was compared to the commonly used approximation of parameter standard deviation $\sigma$ estimated from the least squares optimiser covariance matrix, which is purely a measure of the numerical stability of the result rather than a reflecting the propagation of input uncertainties.

**Table 3: Description of parameter uncertainties used as inputs for the Monte Carlo uncertainty estimate.**

| Parameter | Description | Source |
|---|---|---|
| Gas Calorific value | 0.3% | Metering standards [62] |
| Gas meter temperature | Empirical distribution, approximately 3% median error | EFUS internal and external temperatures |
| Gas meter pressure | Empirical step distribution, -3% to 1% error depending on altitude | OFGEM report [63] |
| Gas volume measurement | 3% median error | MC simulation using gas temperature and pressure error distribution |
| Gas power | Empirical distribution with 3% median error | Combination of gas volume error and gas CV |
| Total power | 3% median error | Combination of gas and electric power error |
| External temperature | Standard deviation 1˚C | Distribution of difference between NWP and MIDAS temperature readings |

For the MC model, 1,000 iterations were performed using the following steps:

1. For each run, a value of $F_T$ was selected from the EFUS distribution.

2. For each run, a percent deviation value for the meter and the altitude was randomly generated from the corresponding Cumulative Distribution Function (CDF).

3. For each run, for each time-step of the power time series, a meter gas temperature percent deviation was generated. The gas percent volume deviation was calculated. Total power deviation was calculated from the percentage (assuming the electricity uncertainty to be zero) and added to the total power time series.

4. For each time-step in the external temperature time series, a temperature absolute value deviation was chosen and added to the time series.

5. For each run, HPLC was estimated using the modified time series.

The distribution of uncertainties calculated by each method is shown in Figure 7. The mean standard error for HPLC from the MC approach is 0.04kW/˚C (15%) and the MC percentage uncertainties are larger than the regression percent standard error but are narrowly distributed, indicating a more robust uncertainty estimate. We conclude that the JCGM-recommended MC method should be preferred to provide more realistic uncertainty estimates, which reflect the distributions of the underlying data.

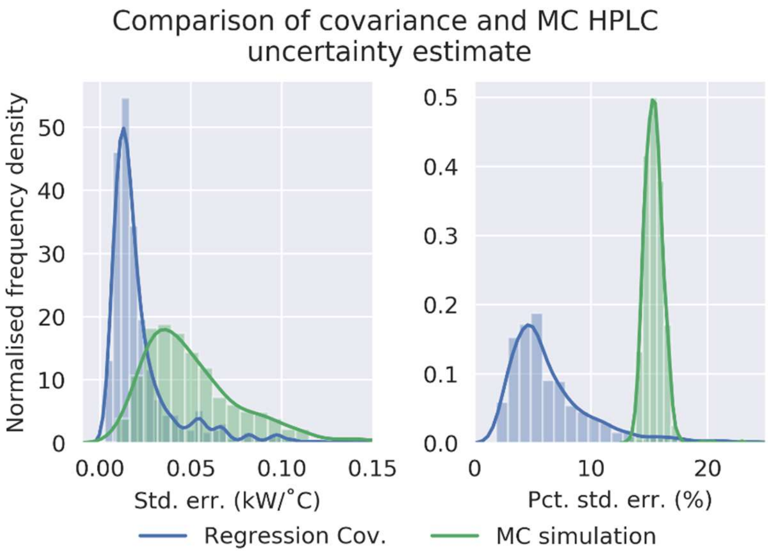


**Figure 7: Distributions of absolute (left) and percent (right) uncertainty in HPLC across 780 EDRP-EDF dwellings, using uncertainty derived from covariance and using MC propagation of input uncertainty distributions.**

### 5.3 Inter-year prediction

To test the predictive power of the model, inter-year comparisons of HPLC and power demand estimates were made. The EDRP-EDF dataset has two years of data covering the 2008-2009 and 2009-2010 winters. HPLC estimates were made for the consecutive years and the predicted and measured energy demand in the second year using model fit from the first year were compared. Year 1 was 2008-08-1 to 2009-08-01 and year 2 was 2009-08-1 to 2010-08-01. Only 170 out of 780 dwellings met data quality standards for both years (no more than 50% missing data points), while 123 dwellings produced HPLC estimates with CVRMSE < 30%.

The HPLC estimates for year 2 against that for year 1 are plotted in Figure 8. The mean difference between the HPLC for the two years was 0% with a standard deviation of 23%, with the regression slope (indicated on the figure) equal to 1. This indicates a good cross-year agreement and supports the notion that HPLC can be a reliable weather-independent and occupant-independent dwelling metric over time. Energy demand in the heating regime (low solar gain period) in year 2 was compared to the value predicted using inferred model parameters in year 1. Figure 9 plots the distribution of results and demonstrates a good agreement between them. A -6% median bias in predicted demand was found with an inter-quartile range of 15%. This indicates that the HPLC can be used to consistently calculate heating demand.

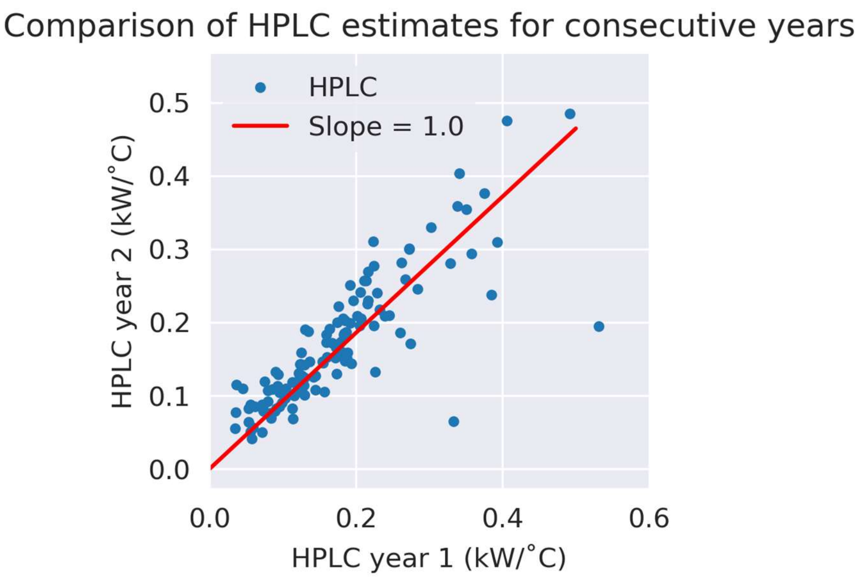


**Figure 8: Comparison of HPLC estimates from year 2 against year 1, with regression line in red.**

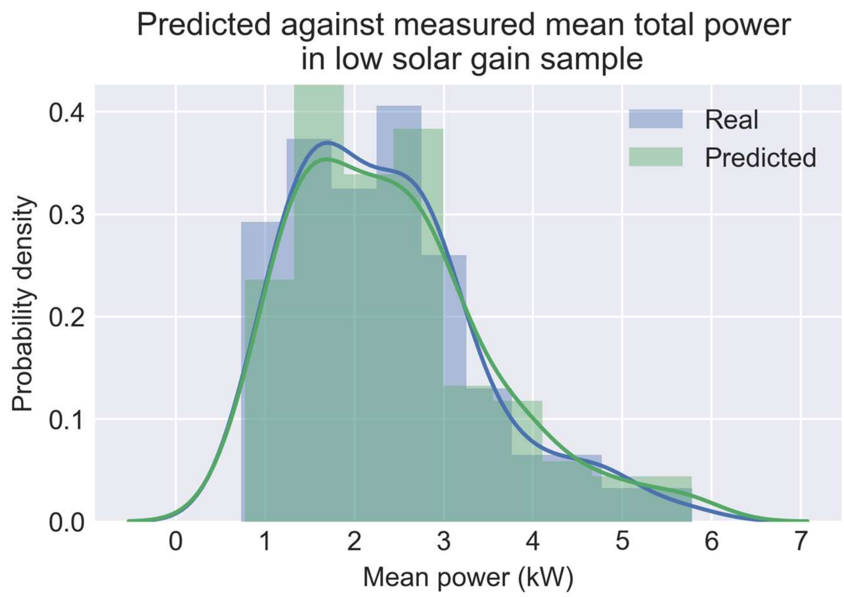


**Figure 9: Predicted and measured mean power demand in year 2 for the low solar gain sample.**

## 6 DISCUSSION

Deconstruct was successful in estimating HPLC for 70% of dwellings with an uncertainty of around 15%, with the value being stable across several years indicating that it is robust to inter-year weather differences and is likely to be independent of occupant effects. This study required dwellings to have at daily average data spanning least one year, with no more than 50% of missing data and no less than 5 data points existing in each sub-sample, together with location. The data collection length is relatively long, however this allows for a simple and robust approach that is a good fit for smart meter data, where there is little control over input data quality or data collection conditions. Accumulating this data is simple if there is a national smart metering infrastructure. In the UK, smart meters already store by default data for 13 months in their internal memory [64]. Deconstruct presents an opportunity to derive considerable value from this data for both utilities and customers, and may also be an important argument to help obtain the required consent from customers to make use of this data. Alternatively, shorter sampling periods could be achieved through a more pro-active data collection strategy, for example by sampling specific periods during winter and summer or controlling the heating system in a structured way (for example using a smart heating system to perform a controlled test when occupants are absent).

The thermal model of the dwelling is by necessity very simple, using a single thermal zone. The HPLC was found to depend on the internal temperature model approximation for $F_T$, but was robust to changes in $\eta_B$, $P_B$ and $T_0$. Thermal bridging or transfer to the ground was not considered, because suitable data is not expected to be collected for most dwellings. Deconstruct only provides estimates of lumped dwelling parameters, which alone are insufficient to predict the effect of specific retrofits (e.g. installing double-glazed windows). However, Deconstruct could be used to detect if retrofits had resulted in the expected change in HPLC.

The HPLC combines the heating system and fabric efficiency. Although these values combined are important for evaluating the overall energetic performance of a building, not being able to separate the heating system efficiency introduces some limitations. Notably, in the case of heating by heat pumps, the inferred HPLC will reflect mainly the high efficiency of the heating system and will not give a good indication of the heat flow through fabric. Nevertheless, it will correctly evaluate heat-pump equipped dwellings as being highly energy efficient overall. Since heat pump efficiency can be dependent on external temperature the HPLC Deconstruct model would need to be adapted to account for this.

Although solar gains are described in the model theory, solar aperture parameters were not considered in this paper. Solar gains would introduce more complex geometric considerations to the model and it would be useful to determine to what extent they may improve the performance of the Deconstruct method in terms of parameter inference and power prediction accuracy. The use of a low solar gain sample alleviated the need to account for solar gains, which was identified as a significant challenge in previous work [32,36]. The resulting HPLC estimates were furthermore judged to be good measures of thermal performance. The effective solar aperture would be an interesting aspect to develop in future research.

The simple temperature model makes a number of fairly strong assumptions. Notably, it assumes that the underlying daily temperature/heating pattern does not change significantly over the days selected for the regression sample. There could be significant changes to the heating schedule related to changes in occupancy. No attempt was made to construct an occupancy model. In theory, it should be possible to develop a method of predicting occupancy level based on energy consumption data, for example by looking for traces of appliance usage in electricity data. However, without a good labelled dataset this is difficult to do with any rigour. It was found that the simple occupancy heuristic was effective and that energy demand follows a reliable pattern across days without attempting to take detailed occupancy profiles into account. The generally good performance of the physical model suggested that occupant behaviour effects may not be significant for HPLC calculations, however in this case an in-depth study of occupant behaviours was not performed. A possible approach for investigating this would be to calculate HPLCs for dwellings with different occupants (for example different tenants in rented accommodation).

One impact of not modelling occupancy is that metabolic gains are not accounted for and are assumed to be stable and non-correlated with weather. Smart thermostats could provide valuable additional information in this regard, as they are usually designed to adapt heating patterns to occupancy and do so by using a range of methods to predict occupancy, such as drawing on data from smartphone apps.

Wind speed might be expected to have an impact on energy demand but was not included in the thermal model as preliminary analysis demonstrated that there was no significant dependence of power demand on absolute wind speed. Similarly, precipitation was not found to be correlated with power demand once temperature and solar gains were taken into account.

Secondary heating systems are used in 48% of UK dwellings [45], these are predominantly gas or electric. Since the energy use of these heating systems is metered there is no need for special consideration for the dwelling energy balance. This highlights the importance of using total metered energy demand to capture all heat sources. Approximately 10% of dwellings use solid fuel or 'other' supplementary non-metered heating systems. It is not possible to model the contribution of non-metered energy to the thermal balance.

# 7 CONCLUSION

Using the Deconstruct method it was possible to infer dwelling Heat Loss Coefficients (HPLC) with a median value of 0.28kW/˚C and uncertainty of 15%, using daily average smart meter data for one year and dwelling location. A good agreement was found between the inferred HPLCs and the coefficients provided by the CHM which were calculated bottom-up from building surveys. This demonstrates the ability to non-intrusively estimate an indicator of thermal performance of a dwelling. The method was demonstrated to work on a relatively large datasets (over 700 buildings). This was possible thanks to the post-hoc control trial approach, which used the simplicity of accumulating smart meter data over long periods to extract sub-samples optimal for estimating the HPLC. These results suggest that HPLCs calculated using Deconstruct could form part of an 'empirical EPC', which could assess the as-built performance of dwellings.

A UK nationally representative mean value of internal-external dwelling temperature slope parameter $F_T = 0.17$ was found using EFUS data. This value contributes to the calculation of the HPLC, and was found to be a reasonable approximation for most dwellings, enabling estimates of HPLC without the need for internal temperature monitoring. The EDRP-EDF dataset used in this research and therefore the derived HPLC values were not nationally representative. In the future a nationally representative sample such as EFUS could include smart-metered data and hence determine a nationally representative estimate of as-built dwelling thermal efficiency. The Smart Meter Research Portal (SMRP) is being developed to provide this type of data, which combined with Deconstruct will provide valuable insights into building thermal performance for the research community [65].

The UK government plans to enable access for companies and research to dwelling smart meter data through the Data Communications Company (DCC), where occupants have provide opt-in consent, facilitating easy access to large volumes of dwelling energy data in terms of number of dwellings and length of period for which data is collected. The Deconstruct method is ideally placed to take advantage of this data source to provide thermal performance estimates for dwellings and provide additional value from meter data for utilities and occupants. Using such data sources would allow HPLC estimates for connected dwellings to be updated each year. This could be relevant to support energy policy making at the national or regional level by helping track the effect of policies over time. Measuring the impact of dwelling retrofits could be particularly useful for consumers, who could thereby obtain evidence of the effectiveness of their energy retrofit investments and could enable performance-based retrofit contracting.

The Deconstruct method demonstrates cost-effective performance analysis on a large scale. This approach is flexible and open to the incorporation of new data streams generated by the ever-increasing diversity of smart devices, appliances, and sensors. As such, it should offer a sound base on which to build further research and analyse new datasets. The ability to measure dwelling thermal performance on a large scale in a cost-effective manner could offer up-to-date information for occupants to assist retrofit decisions, as well as help track the impact of policies across the building stock. These factors would help reveal the inherent value-for-money of energy efficiency investments - undoubtedly the simplest and most cost effective approach to reducing greenhouse gas emissions and supporting a sustainable energy system, and also one with the most untapped potential.

## 8 ACKNOWLEDGEMENTS

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