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Determining of the role of ventilation in residential energy demand reduction using a heat-balance approach

P. Cosar-Jorda

School of Architecture, Building and Civil Engineering, Loughborough University, UK

R. A. Buswell¹

School of Architecture, Building and Civil Engineering, Loughborough University, UK

V. A. Mitchell

Loughborough Design School, Loughborough University, UK

Abstract

Ventilation in domestic buildings can have a significant impact on energy consumption but it is notoriously difficult to quantify, requiring physical test methods that are cumbersome and costly to apply. Energy demand reduction analyses routinely neglect the impact of ventilation and so offering well balanced advice for specific households is not possible. This paper describes a simple steady-state, heat-balance calculation method that is supplemented with monitoring data to model the effectiveness of reducing ventilation rates to minimum standards for individual homes. A key step is to determine the daily mean air change rate and the method is shown to yield plausible estimates that can then be used to establish the impact on energy demand. The benefits of the approach include improved energy demand disaggregation, customised energy demand reduction assessment and offers a means to underpin the development of better models of ventilation for building performance analysis.

Keywords: Smart home, heat balance, window opening, energy demand reduction, Indoor Air Quality

¹Corresponding author - email address: r.a.buswell@lboro.ac.uk

1. Introduction

Decreasing domestic energy demand in the UK is a key component in reducing CO₂ emissions and providing energy security (Baruah et al., 2014). 29% of the national demand can be attributed to the domestic sector (DECC, 2017) and the UK is set to increase the electrification of heat supplied through resistive heating and heat-pump systems (Clegg and Mancarella, 2018). The reduction of energy demand will continue to apply to electrified systems and from the householders perspective, probably more so during the transition as electricity costs for energy are likely to increase (Baruah et al., 2014). The appetite for economy in the home may well increase alongside the need for greater control of demand (Eyre and Baruah, 2014).

Space-heating generates the largest demand for energy in the domestic buildings (DECC, 2017). Ventilation is responsible for a significant proportion of this (Southall, 2018), but it is also a critical factor in the provision of comfortable and healthy indoor environments (Chenari et al., 2016). Implementing the trade-off between energy demand and indoor air quality presents a conundrum to householders who currently have no simple methods available with which to judge the cause and effect of control actions. Enabling the provision of insightful feedback to support better decision making is therefore an important and useful step forward, but one that has not been fully addressed (Wilson et al., 2013; Hargreaves, 2018).

Interest in the assessment of ventilation began in the 1930's and remains the subject of contemporary research (Persily, 2016; Carrilho et al., 2016; Gough et al., 2018), however the spotlight typically falls on the measurement of ventilation rate, rather than the impact of ventilation on energy demand. Common measurement techniques include the blower door test (Lipschultz, 1981; Coxon, 2013), the use of tracer gas (Marley, 1935; Warner, 1940; ISO, 2012), and more recent approaches such as steady-state analysis of CO₂ concentrations (Persily, 1997; ASTM, 2012).

Field measurements are expensive to deploy, even with the development of

low cost tracer gas methods. They are intrusive and the reliability of these approaches has been questioned (Grot, 1979; Dietz et al., 1986; Sherman, 1989). Studies are often limited providing a snapshot of information relating to infiltration and ventilation rates, rather than characterisation over a wide range of
35 building operating conditions (Zhai et al., 2015; Omrani et al., 2017).

Modelling techniques have been used to study dependency of air change rates on temperature difference, wind speed and window opening (Dick et al., 1949; Liu et al., 2018). They can be applied to provide airflow and thermal load information by application of Computational Fluid Dynamics, but are often
40 limited by the application of fixed boundary conditions (Djunaedy et al., 2003). Common building simulation tools are known to be limited when modelling naturally ventilated buildings where the occupant plays a significant role in determining window operation, effecting the reliability of energy consumption estimates (Carrilho et al., 2016; Yu et al., 2011). None of these methods are
45 practical to implement in residential buildings *en masse* and all have limited capacity to accurately represent the air flow in real buildings even with lengthly calibration procedures.

To complicate matters, natural ventilation in domestic buildings results in time varying flow rates which may not be delivered along intended paths through
50 the building, potentially reducing the effectiveness of ventilation and increasing heat losses (Southall, 2018). The human is a complicated actor in the ventilation control system, where reliable cause and effect relationships between temperatures (for example) and actions are often absent (Chenari et al., 2016). Indeed, anthropological-based energy demand reduction research (Shove and Warde,
55 2002; Pink et al., 2015) evidences the social and circumstantial complexity that overlays more traditional notions of the occupant as an actuator of control as inferred by work such as that of Yun and Steemers (2008), Haldi and Robinson (2011) and Wei et al. (2014).

The ability to evaluate the Air Change Rates (ACRs) in a building has value
60 for the improvement of building energy modelling, providing insight indicators for indoor air quality and for the disaggregation of energy demand. The latter

case is particularly important when trying to engage householders to moderate/change ‘behaviour’ (or the way in which they do things), to routines or practices that might lead to a reduction in their energy consumption.

65 Providing feedback has been demonstrated to yield significant variation in effectiveness (Abrahamse et al., 2007; Abrahamse and Steg, 2009), even to the point of being counterproductive (Herrero et al., 2018). The challenge is to enable the householder to relate their actions to the resultant energy demand, which is more likely to be improved using personalised information (Hargreaves, 70 2018). The assessment of the impact of ventilation forms a key component in this because heat flow through air exchange is difficult to comprehend to the non-specialist. The problem of quantifying the impact of ACR on energy consumption requires non-intrusive methods for its estimation under normal conditions in the home, such that the influence of the occupant on energy demand through the operation of systems can be implicitly captured over varying 75 environmental conditions and then effectively relayed to the occupant.

Building on previous work (Cosar-Jorda and Buswell, 2015), this paper demonstrates the feasibility of using a new hybrid-heat balance (HHB) approach to do this. It combines steady-state modeling with monitoring data to generate 80 estimates of daily mean ACR which can make use of smart-meter data, supplemented with common smart-home measurements. The paper describes the method, verifies the estimates of ACR generated with established norms and then applies the approach to creating indicators of the impact of ACR on energy consumption and potential for energy demand reduction, customised for 85 individual households.

2. The Hybrid-Heat Balance (HHB) approach

Buildings are dynamic thermal systems driven by environmental conditions that vary. They are effected by the gains from heating, hot-water and electrical systems, occupants and the interaction of ACR through stack effect, wind effect, 90 mechanical systems and the associated pressure and resistance characteristics

of gaps, cracks, windows, doors, ducts and vents. The thermal mass of the building plays a significant role in heat storage and all of these factors combine through time constants that vary from the order of seconds to days to yield the observable building energy performance characteristics.

95 A common assumption used to simplify calculations is to consider steady-state conditions, where all driving inputs that affect the heat flow between the building and the external environment do not change with time. In addition, if the assumption is made that all heat gains are evenly distributed throughout the building, and that the internal temperatures are uniform in all zones, then
100 over a period of time over 24 hours the heat transfer through the fabric will approach steady-state (CIBSE, 2006). Under these conditions, a building can be modelled as a single zone and yields the following relationship (CIBSE, 2006),

$$r = Q_g + Q_e + Q_s + Q_p + Q_f + Q_v, \quad (1)$$

where Q_g , represents the heat gain from space-heating from all sources, central heating systems, stand alone fires etc. Q_e are the heat gains from all
105 appliances and electrical heating appliances. Q_p and Q_s are the heat gains from the occupants and solar heat gain through the windows. Q_f and Q_v are the heat gains through the building fabric and ventilation. r is the residual and if we assume steady-state conditions, then the heat stored in the thermal mass is constant and $r = 0$.

110 The heat balance is applied to sensible heat only and the assumption is that there is little difference between indoor and outdoor humidity (comparing daily average values) and hence the latent component of the total heat transfer is neglected. This will be the case in an empty building where there are no processes that generate water vapour (bathing and cooking for example). In
115 the real case, the occupancy will vary and bathing will take place over relatively short periods and are intermittent over the day. Bathing and showering will produce the greatest amount of water vapour and hence the largest input of latent heat, but typically this is contained within the bathroom and extracted

via mechanical means and so it will have little effect on the bulk-average daily
120 mean indoor air temperature in the building.

The heat balance is performed using daily mean or total values (dependent
on the variable). This assumes that there are no effects from the thermal storage
of the fabric over a 24 hour period, which is reasonable when the space-heating
system is operational, after the initial two or three days after its activation. At
125 this time the building fabric has absorbed enough heat to dampen the effect
of heat storage: over the 24 hour period, it will release heat when the heating
system is switched off and recharge once it is activated. Our observations sup-
port this for consecutive days of use when the heating is on for two or three
substantial periods in the day as is the norm in UK households (Kane et al.,
130 2015).

It is important that all sources of heating are captured and where these
are either fueled by metered gas or electricity in order for the the method to
accurately account for the heat input. Care must be taken where standalone
LPG or solid fuel heating devices are used, as these will generate heat input
135 that cannot be readily quantified. Food preparation, whether electric or gas,
will result in sensible heat input to the space: generally cooking is a fairly small
fraction of the energy used for heat (nationally in the UK around 2% (BEIS,
2017)).

All parameters of the model can be estimated using established relation-
140 ships that are adapted to region: for example in the UK the BREDEM model
(Henderson and Hart, 2012) provides a baseline set of assumptions and mod-
els that can be used to characterise a building. It will however yield a very
generic representation of a specific building because of the generalised assump-
tions contained within it. The idea behind the HHB method proposed here, is
145 to replace assumptions with calculated values using local weather data, smart
meter and/or ‘smart home’ measurements from a specific home to create a more
accurate representation of the household’s energy use.

2.1. Description of model parameters

In this work, Q_g is derived from daily metered gas consumption. The metered volume of gas is converted to heat assuming a calorific value (Nationalgrid, 2018) and the (model dependent) boiler efficiency (HHG, 2018). Hot water is treated as a special case. The hot water production was monitored using a heat meter, and it is assumed that this heat either exits the building via the drain, or via the bathroom extract fan and so does not contribute to the daily mean indoor air temperature (Buswell et al., 2013).

Q_e is also derived from daily metered consumption. In this study it was measured every minute using a current transducer on the incoming power supply and aggregated to give daily consumption. It is assumed that all electrical loads result in heat gain in the building. This is reasonable since the majority of energy consumed by most appliances will be converted into heat that will be convected into the space. Radiative and sound-borne components will be partially absorbed by the fabric and be convected back into the space within the 24 hour period (Hosni et al., 1999). Note that the power used for electric water heating (commonly showers) needs to be removed from the daily metered total.

Q_s is calculated using the BREDEM method, based on solar radiation collected from a MIDAS weather station located at Sutton Bonington, four miles from Loughborough. The glazing area for each house was estimated from measurements taken in each home. The frame factor, dwelling solar access and glazing transmission factor were quantified based on the building element characteristics and the standard values used in the BREDEM modelling tool (Henderson and Hart, 2012).

Q_p was estimated based on self-reported daily occupancy patterns and an assumed metabolic rate based on the occupant age and gender, CIBSE (2005).

Q_f was calculated assuming U-values based on the construction ascertained through inspection. A site survey yielded dimensions and fabric upgrades such as double glazing, loft and cavity wall insulation. The driving temperatures in the calculation were daily averages, established from the local MIDAS weather

station and the bulk-average daily mean indoor air temperature in each house,
 180 derived from measurements in several rooms. The measurements, model pa-
 rameters and their sources are summarised in Table 1.

Table 1: Measurements and model parameters used in the HHB method.

Parameters	Approach and reference.
Gas (space heating and hot water supply)	
Gas volume	Measured
Gas calorific value	Taken from the gas supplier, National Grid 2013 (Nationalgrid, 2018)
Hot water volume	Measured
Cold water temperature	Measured
Hot water temperature leaving the boiler	Measured
Water heat capacity	Constant
Boiler efficiency	Taken from SEDBUK based on boiler model (HHG, 2018)
Drain water temperature	Taken from previous LEEDR work, based on ambient conditions (Buswell, 2013)
Electric input	
Power	Measured
Heat gain	Assumed for steady-state conditions based on previous work (Hosni et al., 1999)
Solar gains	
Vertical solar flux	Taken from BREDEM based on location (Henderson and Hart, 2012)
Conversion factor	Taken from BREDEM based on glazing orientation (Henderson and Hart, 2012)
Solar Radiation	Collected from local MIDAS weather station
Frame Factor	Taken from BREDEM based on frame type (Henderson and Hart, 2012)
Glazing transmission factor	Taken from BREDEM based on glazing type (Henderson and Hart, 2012)
Windows area	Site measurement
Orientation	Taken from Google Earth based on building position
Latitude	Taken from Google earth
Monthly solar declination	Taken from BREDEM based on the month of study (Henderson and Hart, 2012)
Occupants	
Metabolic factor	Taken from CIBSE guide based on occupant age and gender (CIBSE, 2006)
Number of occupants	Self reported
Occupied time	Self reported schedule
Fabric	
Building element transmittance	Taken from Building Standards based on building elements' characteristics (BEng et al., 2003)
Building element area	Site measurement
Indoor air Temperature	Calculated from available room measurements
Outdoor air Temperature	Collected from local MIDAS weather station
Dwelling floor area	Site measurement

2.2. Estimating ACR

Once the above parameters have been established the only unknown is the heat flow via air exchange with the outside. Q_v (kWh) is the daily heat gain
185 to the building through ACR and can be estimated over any period of time. In this work the assessment was carried out over 365 days. The daily mean ACR, $\bar{N}$ (h^{-1}), can then be estimated by,

$$\bar{N} = \frac{3Q_v}{24V(\bar{\theta}_{ai} - \bar{\theta}_{tao})}, \quad (2)$$

where V is the volume of the house (m^3), $\bar{\theta}_{ai}$ and $\bar{\theta}_{tao}$ are the bulk mean, daily average indoor air temperature and the daily average outdoor air temperature
190 ($^{\circ}\text{C}$) respectively.

2.3. Measurement and monitoring

The dataset that supports this work together with a full description of the measurement devices, calibration details, data visualisation etc. can be freely downloaded (Buswell et al., 2018). The data from 2013 was used in this study
195 and was obtained via three systems: hot water monitoring comprising an in-line turbine meter measuring hot water volume ($\pm 10\%$) and water temperatures entering and leaving the boiler at one second intervals ($\pm 0.47^{\circ}\text{C}$); gas consumption measured by capturing images of the meter dial every second and converting the dial rotation into an angular displacement over time, from which the equivalent
200 volumetric flow rate of gas was inferred (Buswell, 2013); and a proprietary wireless (Zigbee) system which comprised: Passive InfraRed sensors that measured activity as a binary event and air temperature ($\pm 0.47^{\circ}\text{C}$); current transducers which monitor power consumption by inferring current flow and ‘smart plug’ devices that monitor appliance electricity consumption ($\pm 10\%$).

205 The opening of windows and external doors were also recorded as a time stamp registering a binary event (open/close) through magnetic contact sensors and reported via the Zigbee system. A subset of windows were monitored in each house and these were selected based on discussion with the householders, being asked to select the window which was most frequently used in each room

210 and which windows are ‘never’ opened. Table 2 gives the numbers of windows and doors monitored for each house. The window open time was calculated by aggregating the total number of hours of open time per day, from each window and external door divided by the total number of monitored channels.

Table 2: Number of channels used to monitor window and external door opening.

Number of:	H05	H10	H30	H37	H39	H46
Monitored windows	6	4	9	8	3	8
Monitored doors	2	2	2	2	2	2
Available data (days)	82	68	132	64	37	131

A filter was applied to the data to ensure that all measurement channels required for the calculations were available each day (Table 1). The systems used in this study were a combination of off-the-shelf and purpose made devices, and some were less reliable than others. Data was lost through loss of power in battery charged equipment and powered devices, including communication hubs being inadvertently switched off by householders. Further information can be found in Buswell et al. (2017).

2.4. Sample description

The properties were detached and semi-detached and constructed between 1930 and 1990 with typical brick and block wall construction and tiled roofs. Although a modest sample, they are representative of those found throughout the UK: owner occupied dwellings represent 64% of the UK population and cohabiting couples with dependent children account for 37% of the owner occupied dwellings (DCLG, 2016). The wider LEEDR sample was selected broadly around the following criteria:

- owner occupied family homes;
- have an interest in reducing their energy demand;
- be willing to have their homes monitored; and,

Table 3: Summary of the building and household characteristics. ‘D’ and ‘SD’ denotes detached and semi-detached properties, all of which have 2 floors.

House code	Year built	House type	House size	House insulation	Glazing type	Boiler eff.	Number of appliances	Number of occupants	Weekdays occupied	Indoor temp.
H05	1940	SD	117 m^2	Insulated cavity, loft (200mm)	Double	87%	34	3	1	18.0°C
H10	1980	D	167 m^2	Insulated cavity, loft (>250)	Double	90%	39	4	5	19.0°C
H30	1950	D	111 m^2	Solid wall, loft (none)	Single	90%	33	2	5	17.8°C
H37	1970	D	140 m^2	Insulated cavity, loft (150mm)	Double	90%	37	4	5	18.7°C
H39	1950	D	110 m^2	Solid Wall, loft (> 250mm)	Double	78%	42	4	1	17.5°C
H46	1990	SD	148 m^2	Insulated cavity, loft (200mm)	Double	91%	49	6	5	21.2°C

- be willing to participate in recorded interviews and other activities.

A subset of six homes were selected for this study based on:

- availability of the requisite data;
- heating and hot water were delivered by combination boilers;
- a range of ages of construction types and internal conditions; and,
- a range of family sizes/ages.

The characteristics of the resultant sample are summarised in Table 3. Most households were occupied by at least one person throughout the week due to only one parent being in full time employment, or part-time working, working from home, retirement or unemployment. The sample includes a single parent family with one child (H30); a multi-generation family home with four children, parents and grandmother (H46); three houses with four family members (H10, H37, H39) and one house with three (H05). The home owners were in their late forties to late fifties and all were middle to high income families with education backgrounds up to post-graduate level.

Semi-structured interviews supplemented with informal communication were used to explore the ventilation practices in more detail. These were designed to encourage reflection on window and door use. A summary of the key characteristics that were reported were:

- H05 reported opening windows constantly (during night and day) and regularly opening the back door to ‘allow the outside to come in’ and to give

the dog free run of the garden. Several windows were often continuously opened and the back door was opened for as long as 13 hours a day, when the space-heating was operational.

- H10 reported that they hardly ever open windows. The only window used was the bathroom window to let the water vapour out after showering or bathing but not if the weather was very cold, when a dehumidifier was used instead.
- H37 reported that they implemented a rigorous and structured ventilation strategy to ‘air the house’. Windows were carefully selected and opened every day for around one hour, especially during the weekends. This activity was informed by one of the adult householders who was an expert in natural ventilation design and modelling.
- H46 reported opening bedroom windows in particular. This was driven by the need to reduce ‘bad odour’ and led to bedroom windows slightly opened for the whole day, only closing before going to bed.

These features are readily evident when window and door opening are plotted (Figure1). The orange bars show the front and back door operations and the blue, the windows in the key rooms in the homes. The total duration each element remains open every day was aggregated in hours and plotted as a single point (solid square surrounded by a square box). Repeated actions are shown by denser collections of points ($0 - 5\text{hday}^{-1}$ for the front door in H05, for example). Some elements have two node clusters (H37: Bed.1), or even three (H46: Bed. 2).

Figure 1 should be viewed in conjunction with Table 2 because the interpretation of the plot is affected by the number of samples available, 68 for H10 and 131 for H46, for example. However, the key features to draw attention to are: the extent of the opening of the back door and the general maintenance of open windows in H05; the lack of operation of the windows in H10; the regular, grouped and compact opening characteristics in H37; and significant opening

Figure 1: Window (blue) and door (orange) opening duration for H05, H10, H37 and H46 during the heating season in 2013.

activity in H46, particularly in the bedrooms.

3. Evaluating the Hybrid-Heat Balance (HHB) method

The work reported here formed part of a larger multi-disciplinary study to
 285 establish the landscape of daily life in the home as it relates to energy demand
 and demand reduction. A governing principle was to cause the least disturbance
 to the occupants as possible during the study, which combined with safety concerns
 (Gough et al., 2018), meant that intrusive methods of verifying/validating
 the method were impractical.

290 The approach taken was to estimate the daily mean ACRs for each day
 of available data in 2013 for each of the six households. The magnitude of

these estimates were compared to established norms for these buildings and correlations of ACR with wind speed and window opening were verified against observed and reported behaviour from the interviews.

295 3.1. Results

Since the calculation (Equation 2) of $\bar{N}$ is dependent on the internal/external temperature difference and the sensitivity of the estimates to the available temperature difference was tested using uncertainty analysis. It was found that reliable results were generated when the temperature difference was greater
 300 than 5K. The practical implications of this are depicted in Figure 2 where the upper plot presents the daily mean outside air temperature (black line) and the daily mean internal air temperatures for all of the dwellings studied here (blue). The lower figure plots the temperature difference (orange) and the 5K threshold (dashed line). The colder winter (to the left) can be seen, and this increases the
 305 temperature difference, as one might expect.

The days that fall below this line are rejected and these tend to be during summer and swing seasons. There is also evidence of heating systems being switched off over holiday periods (red circle), causing the internal temperatures to drop and the temperature difference to fall below the 5K threshold. The
 310 implications for estimating $\bar{N}$ is that the bulk of the available data tends to be in the cooler months when the heating system is active.

3.2. Estimates of ACR

The minimum, maximum and average ACRs were calculated using the available data for each household over 2013 and are presented in Table 4. Note that
 315 the number of data given in Table 2 are the total available for analysis after the 5K criterion has been applied. The uncertainty in these values was calculated by propagating the uncertainty in the measurements and any parameter through the calculation (Coleman and Steele, 2018).

The average ACRs vary from 0.5h^{-1} to 2.6h^{-1} which corroborates the work
 320 of others (EST, 2014; Bedford et al., 1943; Fabi et al., 2012), and are within the

Figure 2: A comparison of the temperature difference between the daily mean indoor air temperature and the daily mean outdoor air temperature to the 5K threshold, below which the difference is considered too small to yield reliable estimates of ACR. The upper plot gives the temperatures and the lower, the temperature differences with the threshold. The red circle highlights one house where the heating was switched off for a significant period, causing the internal temperatures to decay towards the external air temperature.

bounds of uncertainty of the estimates found by Wallace et al. (2002). Minimum values, when it might be expected that windows and doors are kept closed for the majority of the day, were below 0.1h^{-1} , although the uncertainty in these estimates is relatively high. The upper end of these limits might suggest that
 325 0.4h^{-1} to 1.3h^{-1} are within the uncertainty in the minimum rates observed. Maximum values observed ranged from 1.2h^{-1} in H10, a house who rarely opens windows to 9.8h^{-1} in H05, who regularly have all windows open. High values (up to 30h^{-1}) have also been observed by Sheldon et al. (1989) and Bedford et al. (1943).

330 The ventilation model within BREDEM was used to calculate the daily mean ACR for each house on the same days as for the HHB method using the

Table 4: Minimum, average and maximum ACRs (h^{-1}) estimated using the HHB method for the available data in 2013.

Household	Minimum	Average	Maximum
H05	$< 0.1 \pm 0.9$	2.4 ± 0.4	9.8 ± 2.0
H10	$< 0.1 \pm 0.9$	0.5 ± 0.3	1.2 ± 0.3
H30	$< 0.1 \pm 0.5$	1.9 ± 0.6	7.1 ± 6.2
H37	$< 0.1 \pm 1.0$	2.1 ± 1.4	6.3 ± 3.4
H39	$< 0.1 \pm 0.8$	2.0 ± 0.6	7.4 ± 6.9
H46	$< 0.1 \pm 0.4$	0.6 ± 0.3	1.8 ± 1.5

local daily mean wind speed measurements from the MIDAS weather station at Sutton Bonington to drive both calculations. The average ACRs from BREDEM were between 0.5h^{-1} and 1.3h^{-1} . The households in this sample with higher
335 ventilation rates were underestimated by BREDEM (H05, Table 4), and those who used less ventilation were overestimated (e.g. H10).

3.3. ACR correlations

Data from four households (H05, H10, H37 and H46) were plotted in two figures: one that gives ACR as a function of wind-speed (Figure 3) and the other
340 as a function of window open time (Figure 4). Linear least squares regression has been used to characterise the relationships, represented by the blue line in both figures. The orange line in Figure 3 represents the equivalent ventilation characteristic as described by BREDEM adjusting for each building.

Although the correlations between ACR, wind speed and the duration of
345 window opening are weak, there are observable differences between households. Three user types can be identified based on their use of windows: H10 (and H39) who rarely open windows (which we call here, rare operators); H37 and H46 (and H30), who open regularly 1-5 hours a day (regular operators) and H05 who opens frequently and for long periods (extended operators). The opening
350 time influences the range of household ACRs, resulting in values between 0h^{-1}

Figure 3: Correlation between ACR and wind speed. Linear regression least squares models shown as a blue line and the orange line is the equivalent model predicted according to BREDEM for the specific building type for each home.

and 1h^{-1} for rare operator households, 0.5h^{-1} to 2h^{-1} for regular operators and 1.5h^{-1} to 3h^{-1} for the extended operator households.

This observation is in the line with previous research, which highlighted the strongest influence on ACR of window opening, reporting an increase of 2h^{-1} for extended opening time (Wallace et al., 2002). H37 is the only house that shows any correlation with window operation. Two clusters of data around 1h window^{-1} and 2h window^{-1} are evident. By extrapolation this implies an infiltration rate of 0.78h^{-1} , which is similar to the average suggested by BREDEM, 0.7h^{-1} , and also the minimum ventilation rate for a healthy indoor environment of similar characteristics (ODPM, 2010).

Figure 4: Correlation between ACR and window open time with a linear regression least squares model shown as a solid blue line.

4. The impact of ventilation on household energy demand

The HHB technique is applied here to a hypothetical energy demand reduction modelling exercise to demonstrate:

- the degree of customisation of analysis to individual households that can be generated;
- the potential for the disaggregation of energy demand and householder reduction guidance that can be created; and,
- the scalability of the approach by mounting the method on pre-existing smart meter/home monitoring systems.

370 A sample of homes were treated individually taking the state of the building
as it was surveyed prior to the collection of the monitoring data and applying the
energy demand reduction models to each specific case. The configuration of the
smart monitoring devices in each home were different and hence the application
of the method was not only adapted for the condition of the building fabric,
375 heating systems and the occupant activity, but also for the available data: a
critical requirement needed to apply such a technique to many buildings.

4.1. The approach to the analysis

The analysis was based on data over a whole year (2013). The data available
for the analysis varied between 100 days (H39) to 246 days (H46) out of 365,
380 and so the results were scaled up to yield annual energy reduction values by
averaging week day and weekend day values in six, two month periods (Jan/Feb,
Mar/Apr, etc). These are then multiplied up by the appropriate number of days
in the period such that the sum is over 365 days.

A literature review determined a list of interventions that impact building
385 energy demand and of these, four were selected to demonstrate the application
of the method. These were minimising ventilation to provide the minimum
stated in the building regulations, increasing the insulation levels of the building
fabric to the current building regulations standards, installing triple glazing and
heating the interior to a maximum temperature of 17°C (Boardman et al., 2005;
390 Ben and Steemers, 2014; DTI, 2007; Loveday et al., 2008; Energy Saving Trust,
2011; Shipworth et al., 2010; Hall et al., 2013; TSB, 2013; Banfill et al., 2011a;
Mata et al., 2010; Boardman, 2007; DTI, 2007; Moon and Han, 2011; Martinaitis
et al., 2015; Hong et al., 2006). Implementing the interventions to the stated
levels are unlikely to be achieved in practice, but they represent what might be
395 considered to be a ‘theoretical limit’ to energy demand reduction which allows
the greatest potential impact to be evaluated.

The intervention models are applied to either the data components, or the
modeled components of the approach as appropriate. Reducing space-heating
set point temperature is applied to the measured room temperatures at the

native sample interval of the data (1 minute in this case), which allows very specific effects of interventions to be represented. The filtered, or modified data is then aggregated/averaged to yield daily values and then used as the new input to the heat balance calculation in the HHB method. The upgrade of insulation and triple glazing were represented by adjusting the U-value parameters in the steady-state fabric heat loss calculation, where the appropriate heat losses are calculated on a daily basis, prior to the heat balance calculation. Adjustment to the ACR was implemented by modifying the daily estimates of $\bar{N}$.

The flexibility in the analysis the method offers is in the extent to which measures are applied in a particular household because it can be modified through the adjustment of the model parameters. In addition, because the data collected from each household implicitly captures their daily routines and activities, the analysis of the impact of any measure, or group of measures, are automatically tuned to that specific household. The analysis is executed in four stages:

1. Run the HHB method over the available data to derive Q_v and then $\bar{N}$ for each day.
2. Apply intervention models to estimate the resultant energy consumption, first Q'_e (to account for internal heat gains) and then Q'_g .
3. Calculate the daily energy reduction $Q_{g_{reduction}} = Q_g - Q'_g$, and likewise Q_e .
4. If 365 days of data are not available, scale the reductions calculated on the available data up to yield an annual figure.

4.2. Results

The results from modelling each measure in isolation were ranked based on the average energy reduction achieved throughout the sample, Table 5. The largest reductions for each house are highlighted in bold text. Wall insulation ranked first on average and minimising ventilation fifth. The impact of wall insulation was particularly high in two houses, H30 (30% reduction) and H39 (64% reduction), which are both detached properties with solid wall construction. Similar figures were found by Banfill et al. (2011b), suggesting a 60% to

430 71% potential reduction was possible by applying retrofit measures to a solid wall house. The difference in the potential reduction between these two solid wall houses might be partially attributed to larger impact of ventilation on H30, tempering the impact of the insulation.

Table 5: Ranking the energy demand reduction potential of each measure in isolation in each house. The figures show the reduction based on the 2013 data (MWh/year) and as a percentage (in parenthesis). The measures that yielded the largest reductions are identified in bold for each house.

Rank	Reductions	H05	H10	H30	H37	H39	H46
1 .	Fabric insulation	2.7 (10%)	4.4 (17%)	9.8 (35%)	3.3 (13%)	14.8 (62%)	2.2 (8%)
2 .	Triple glazing	2.4 (9%)	5.7 (22%)	5.9 (21%)	4.3 (17%)	3.4 (14%)	5.6 (20%)
3 .	Heating to 17 °C	4.8 (18%)	4.9 (19%)	3.9 (14%)	4.5 (18%)	2.2 (9%)	7.0 (25%)
4 .	Minimum ventilation	8.4 (32%)	0.2 (1%)	4.7 (17%)	4.2 (17%)	1.2 (5%)	2.6 (9%)

The replacement of windows with triple glazing could reduce energy consumption from 9% to up to 22%. Similar reductions to those from triple glazing are possible from reducing the peak indoor temperature to 17°C. In H46 the maximum reduction is generated by reducing their internal air set point temperature as the daily average air temperature in that home is over 21°C during the heating season, the highest in the sample.

440 The decrease of ventilation would have the largest impact for H05 (32%), which might be expected given the amount of window operation observed (Figure 1). In H37, where windows were thoughtfully operated, a 17% reduction might be possible. The reduction is similar in H30 and H46, which could reduce their consumption by about 9%. At the other extreme, H10 might only benefit from a 1% reduction, because the windows are rarely opened. In fact 445 the analysis was rerun in H10 to represent sealing of gaps and cracks in the fabric and this intervention yielded a higher reduction of 3%, which illustrates the diagnostic capabilities of the approach.

The results are plotted in Figure 5. The format of the plots were inspired by concept work carried out by Human Centered Design researchers collabora- 450

Figure 5: Household consumption and demand reduction data generated by applying the HHB method to six households. Total annual energy consumption is shown by the dark blue bar, the top-right, light blue bar indicates the proportion of the total that is electrical consumption. The other light blue bar (bottom-left) shows the impact of the ventilation reduction measure, and the green bar is the resultant consumption after all reduction measures have been applied.

rating on the LEEDR project (Buswell et al. (2015), p79). The dark blue bar indicates total energy consumption in 2013 and the top-right light blue bar is the proportion of that consumption that is electricity. The bottom-left light blue bar represents the heat energy lost through ventilation (over and above the minimum required for health). The green bar represents the resultant energy consumption if all reduction measures are applied. The national average of 20 MWh for this group of homes is shown by the orange line.

Plotting the data in this way allows the comparison of data important to the information to convey to the householder. In this case, including the total annual energy consumption demonstrates that this sample of six households use significantly more than the national average for their house type. Energy demand reduction and other useful targets can also be illustrated on the plot. Linking this graphical representation directly to the monitoring system database can

provide visualisation of live and historical energy use, together with reduction
465 potential which the householder can readily access to inform them of progress
when trying to affect changes in their energy consumption.

5. Discussion

The HHB method has been demonstrated to provide indicative estimates
of ACRs that are useful for creating more complete energy demand reduction
470 analysis that can be individualised for a household through the use of monitoring
data. Both the significance and the variability of ACR on energy consumption
was demonstrated, underlining the need for its evaluation (Fabi et al., 2012;
Carrilho et al., 2016).

ACRs are influenced by several driving forces: wind, (CIBSE, 2006); window
475 opening (Fabi et al., 2012; Howard-Reed et al., 2002; Kvisgaard and Collet,
1990; Wilson et al., 1996); house characteristics (CIBSE, 2006; EST, 2014);
and behaviour (Zhai et al., 2015). Although the HHB method does not yield
statistically significant correlations, it is capable of identifying those that use
a significant amount of ventilation (H05), those who are particularly frugal
480 (H10) and those in between (the majority). The method also appeared to be
sensitive to differentiate the effects of the systematic operation of windows in
H37 although the reasons for the lack of evidence of effect of window opening
in the other houses could not be determined with certainty. One reason for
this maybe in part connected to the impact of equalising temperatures on the
485 reduction in air flow rate through reduced stack effect (limiting to about 2h^{-1} ,
Wallace et al. (2002)).

The HHB method is sensitive to the internal and external air temperature
difference and a minimum ΔT of 5K is needed to yield reliable results. The
ACRs are evaluated over a 24h period to minimise the influence of thermal mass
490 on the heat balance. Work undertaken in preparation of this article did explore
the estimation of hourly ventilation rates and although there was potential, the
results were less reliable and we suspect that the dampening effect of the thermal

mass influenced the calculation.

The resultant ACRs in homes are affected by factors that the HHB method
495 is insensitive too. The effect of window opening might be harder to evidence
because daily mean ACRs are calculated and the synchronisation and timing
of the openings will effect the effectiveness of the ventilation, but this will be
masked to a degree because of the averaging effects of the means-based estimate.
Not all windows were monitored and there is the possibility of closed doors
500 within the building which will also reduce the sensitivity of the method.

We base the daily mean internal air temperature on a number of room mea-
surements and so the extended opening of one window in a room with a closed
door, and possibly in a room where the temperature does not influence the
calculation of the mean value, will affect the characteristics derived. Care is
505 required if a household has heating appliances that are not connected to the
metered supplies and it is also possible that the location and orientation of any
given window hampers the sensitivity ACR of that opening (Gough et al., 2018).
Further work might look at the influence of these effects in more detail with the
aim of minimising the sensors needed.

510 What is encouraging is that the resulting estimates of ACR agree with other
studies (EST, 2014; Bedford et al., 1943; Fabi et al., 2012) and in particular the
uncertainty of the estimates were of the same order of magnitude as those pub-
lished by Wallace et al. (2002). The ACRs derived from the HHB method for the
regular window users are comparable to those from the BREDEM ventilation
515 model (Henderson and Hart, 2012), but an observation was that the BREDEM
model appears to give poor representation at the extremes of ventilation behav-
ior, i.e. for rare, or extended users. This suggests that neglecting the actions
of the occupant becomes an issue where the idiosyncrasies of energy use in the
home is a significant factor. When undertaking the prediction and assessment of
520 energy demand reduction, misrepresenting the impact of ventilation is likely to
lead to poor advice for the householder. The HHB method avoids this problem
because it can characterise ventilation from non-intrusive data that implicitly
captures the effect of window and door opening on space-conditioning energy

consumption.

525 If the estimates of ACR for the sample presented here are taken at face value, there are potential implications for the attainment of health standards. (ODPM, 2010) suggest 0.5h^{-1} is the minimum required, implying that all but H05 in this sample is under-ventilated for varying proportions of the year. In H10, only 7% of the days tested met this minimum criteria (excepting the limits
530 of uncertainty). A future application for the HHB method might be to alert the householder to potentially unhealthy ventilation practices and guide them in balancing this requirement with the need for minimising space-heating, a difficult trade off to maintain (Dimitroulopoulou, 2012).

The HHB method makes use of smart-meter and smart-home monitoring
535 data and does not require physical testing to estimate daily mean ACR. This makes it *powerful* as it can be used on-line to continually monitor ventilation and *scalable* as it can be applied to any house with requisite monitoring data. As the number of households that have smart monitoring and measurements grows, there is the potential to collect greater information on ACRs throughout
540 the UK and beyond with the HHB method. As the home energy service market develops (DECC, 2012), monitoring and feedback to householders can now include information on ventilation control, which was previously not possible. As the population ages (Hamza and Gilroy, 2011), more of the population will live at home and the need for remote monitoring and balancing the trade of
545 between energy for space-heating and indoor air quality and will become acute. Approaches like the HHB method could contribute to ensuring the health of nations (Deloitte, 2015).

Further work is needed to fully validate the approach, ideally comparing the results to multiple days of data derived from more conventional physical
550 testing such as tracer gas methods. Work might also consider a more systematic evaluation of the influence of extractor fans and trickle vents.

6. Conclusions

A new Hybrid-Heat Balance method that combines steady-state modelling with smart-home and smart-meter monitoring data in order to customise energy demand reduction analysis to individual households has been presented. It was demonstrated that the approach yields credible estimates of daily mean ACRs in domestic buildings. These estimates can be combined with other analysis to create greater insights in home energy consumption and an example of how to apply the method to energy demand reduction analysis was given.

Customised assessment is crucial in the disaggregation of heat and energy demand in the home and the approach demonstrated its sensitivity to identify both the significance *and* variation of ventilation in this process. Average ACRs calculated by the method were shown to vary between $0.5(\text{h}^{-1})$ and $2.4(\text{h}^{-1})$ and the subsequent energy demand can be nearly 60% of the daily demand for the sample observed.

The approach is scalable and robust. It was successfully applied to several households that were different in construction, system type, occupancy and in the configuration of the monitoring systems. Wider implementation of the HHB approach could yield more effective energy demand reduction advice to householders and be used to generate better representations of ventilation for the modelling and simulation of domestic buildings. The in-situ estimation of ventilation rate could also be applied as an indicator of indoor air quality, which could be used to help to create and maintain healthy indoor environments balanced against energy demand.

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