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UNCERTAINTY IN WHOLE HOUSE MONITORING

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ABSTRACT

Monitoring energy and temperatures in dwellings is becoming commonplace due to the reduction in sensing costs. Measurements can be used for informing the occupants on their energy as well as developing better inputs for building performance simulation and verifying analysis. In a home monitoring environment making sense of this data can be difficult as the number of measurements increases; one of the key challenges for the homeowner and for organisations that collect and analysis energy data is understanding what can and cannot be 'seen' in the data. In building simulation, there is a growing interest in applying uncertainty to generate robust model predictions, however there is also a need to understand the uncertainties in measurements used. What is often missed in these analysis is an evaluation of the uncertainties in the measurements in relation to the intended analysis. This paper presents a set of typical domestic energy monitoring measurements that have recently been collected as part of a 4 year research project in the UK. Levels of uncertainty are evaluated and the consequences for typical metrics used in energy and comfort analysis are discussed.

INTRODUCTION

Uncertainty is traditionally associated with the evaluation of bias and random effects on experimental measurements (Coleman and Steele, 1995). Its application to the field of building performance, modelling, simulation and monitoring is an important and developing research area. The value of the uncertainty and sensitivity analysis is being recognised as are the barriers to wider adoption; the lack of information of the uncertainties in the material properties have been recognised by Domnguez-Munoza et al. (2010), for example. The potential benefits of combining techniques such as differential sensitivity analysis and monte-carlo analysis with building simulation tools have been investigated for a number of years (Macdonald and Strachan, 2001). Uncertainties in the early stages of design and developing ways to incorporate these into useful simulation input parameters has been explored by de Wit and Augenbroe (2002) and uncertainty propagation to evaluate energy demand has been explored by Rasouli et al. (2013). Uncertainty has been used in air flow calculations (Costola et al., 2010), to evaluate the quality of simulation prediction and measurement of energy consumption in buildings (Brohus et al., 2009), for the use with probabilistic climate change models (Tian and de Wilde, 2011).

The continual reduction in the cost of sensor technology and the increasing capacity for data communication and storage allows far greater levels of systems monitoring and while in the past, this has been the preserve of HVAC systems in commercial buildings, this is now rapidly spreading to the domestic market. This presents many new monitoring and control opportunities; iPhone Apps from which to control your central heating being one. Not only does a greater level of measurement mean that more data about a building and how people use it can be gathered, but it gives use the opportunity to monitor systems in a similar way to that has been done in commercial buildings (Glass et al., 1994; Kim et al., 2008).

The challenge in monitoring and measurement applications in buildings is the fundamental issue of robustness due to unmeasured/unknown disturbances, often by the interaction of people Breuker and Braun (1998); Buswell and Wright (2004). This is heightened in a domestic setting where the interaction of people and constraints over the placement of sensors play an important role in what can be inferred from these measurements. Typical questions asked are ones to do with the amount of energy that can be attributed to a device, or practice, the heating levels, or comfort in a space, or carrying out energy balances to confirm that the parameters of an analysis are all correctly accounted for. Other questions such as whether energy has been saved after an intervention, or whether 'behaviours' have changed require the consideration of parameters over time, but the robustness of all these calculations can be assessed readily by the application of uncertainty analysis and uncertainty propagation as described by (Kline and McClintock, 1953).

The common barrier to the application of uncertainty analysis is the lack of suitable estimates of uncertainties in variable or a lack of examples of applications to follow, there is very little in the current literature in the building energy field. This paper presents the evaluation of uncertainties in measurements taken from a current domestic energy monitoring project in the UK. Key variables and their uncertainties relevant to building energy analysis are presented and discussed.

BACKGROUND

In 2010, the UK government, through the UK Research Council, funded a number of projects based around reducing energy demand through ICT; the LEEDR project (Low Effort Energy Demand Reduction) was a four year project funded under this programme. The overarching aim of the work was to understand how to develop intervention measures that would have a significant, long-lasting impact on energy consumption in the home and that would require the least effort to implement by the home owner. In recognition of the multi-disciplinary nature of behaviour, energy and technology, the project included expertise from social sciences, design technology, computer science, systems engineering, electrical engineering and building physics. Emphasis was placed on developing a better understanding of energy consuming practices in the home and how this relates to monitored energy consumption. The monitoring regime includes: electricity consumption on most appliances and lighting and power circuits; gas consumption for space heating and hot water production; how water consumption; occupancy in the most significant rooms; internal air and heating system temperatures; and weather data. Gas and hot water consumption in a number of homes is monitored down to a 1 second sample rate and so very detailed pictures of activity can be drawn.

The 20 homes are participating in the project and all are within a 4 mile radius of a market town in the East Midlands of the UK. The homes vary in construction but are typical of there respective years of construction (1900 to 2002) and are typical of those found throughout the UK. All homes are occupied by families that range in number an age, from 3 persons to 6 persons and range from parents with babies to adult children and relatives living together. Most have had some retrofitting of insulation and been living there for more than 4 years, nearly half for more than 10 years.

One of the challenges with monitoring is that all homes are different; gas meters, distribution boards, power circuits, room dimensions, floor plan layouts, use of space, mixed methods of hot water production and cooking, difference appliances, different occupancy and usage pattered, different patterns of energy consumption. The natural variability in the way life is lived in homes presents significant challenges to monitoring and understanding consumption and results in bespoke installations of equipment in every property. This makes developing a unique uncertainty analysis for every home time consuming and so the approach of this paper has been to explore where reasonable assumptions can be made based on one property and applied across homes.

WHOLE HOUSE MEASUREMENTS

The test homes were monitored by a mixture of 'off the shelf' non-research grade equipment and bespoke measurement equipment. Using cheaper devices meant that a) more could be monitored for the available budget, and b) the results are applicable to all properties with similar equipment, making the output more broadly applicable, particularly in terms of the uncertainty analysis. Bespoke equipment was developed for gas and hot water consumption because there were no comparative alternatives available on the market at the time of installation, or because there were installation issues with such devices. The analysis presented here is therefore applicable to those devices specifically, although the uncertainties can be seen as indicative and the approach taken here can be readily adopted for other devices. The presence and door/window open/closed indicators are binary signals and hence are neglected here as are some temperatures used to measure surface temperatures where they are just used as an indicator of whether something is 'getting hotter' or 'cooling down' which was used in some places to help understand heating and hot water system operation. The following details the measurements made and discusses purpose, location and the method of measurement:

Air temperature: Air temperature around the homes were measured by a sensor piggy-backed onto the PIR (presence) sensors. Typically these devices would be wall mounted in a location to capture movement in a room, and hence the temperature measurements will sample the local air conditions. This measurement needs to be used as an estimator for a) air temperature at waist level for analysis of control action/comfort or b) the bulk average air temperature in energy calculations.

Electrical power: Two devices were used. A CT based unit that was used to infer the power consumption in the mains supply. The device uses the hall effect to infer current flow in a conductor, which is converted to power assuming a voltage, an issue is that these are particularly inaccurate measuring very low current, which is not a problem on the mains supply, but more challenging on some of the circuits that tend to have varying and intermit ant loads attached. The second device is a plug load monitor used to measure main appliances and plug based lighting, which give better low current performance than the CT devices. Both measure apparent power and need correcting for power factor to give the real power.

Gas volumetric flow rate: This was measured using a bespoke optical recognition device developed at Loughborough University Buswell et al. (2013). The challenge was to create a measurement device that did not need to attach to the gas meter and that could read gas flow at high frequency. With the device the rotation of a needle was translated into a volumetric flow rate of natural gas, with a smile rate of 1 second. This is used to calculate the heat input to the boiler and ovens/hobs for space heating, hot water production and food preparation, by estimating the calorific value of natural gas.

Water volumetric flow rate: The measurement was made by an in-line turbine flow meter installed in the cold water feed to either the combination boiler, or hot water storage cylinder, depending on the system type installed. These units generate a pulsed output with each rotation of the turbine which is counted and converted to a volumetric flow rate. The turbines were 'off-the-shelf' items, connected to a bespoke flash card based storage device. This device recorded the flow rates at an interval of 1 second, and was also used to measure water temperatures associated with the hot water supply.

Water temperature: The domestic hot water supply temperatures on the inlet and outlet to the boiler/cylinder was sampled every second and stored on the above mentioned device. Combining the flow rates and temperatures is used to calculate the heat supplied to the hot water distribution system. The temperatures are measured using digital thermocouples fixed to the surface of the copper supply pipework with one side exposed to ambient air. This is a practical installation, but there is likely to be a little bias in the measurement as it is used to infer the bulk average temperature of the water in the pipe.

ASSESSING UNCERTAINTY

The uncertainties associated with each of these measurements is discussed in the next section with specific reference to the application in analysis.

Bulk average air temperature

The total uncertainty in the estimation of the bulk average air temperature, U_{θ_a} (K), is given by,

$$U_{\theta_a} = \sqrt{U^2_{\theta_{res}} + U^2_{\theta_{cal}} + U^2_{\theta_{man}} + U^2_{\theta_{bulk}}}, \qquad (1)$$

where $U_{\theta_{res}}$ (K) is the minimum resolution of the device, U_{bulk} (K) is the estimate to how closely the location of the measurement in the room represents the bulk average value, U_{man} (K) is the observed variability in the manufacturing of the devices. In cheaper devices this variation is likely to be higher than more highly specified equipment. While these can be calibrated, when installing many devices, this exercise becomes infeasible and the variations that occur due to the manufacturing process need to be accounted for. Accounting for this uncertainty in calculations is therefore more pragmatic, albeit at the expense of precision. U_{cal} (K) is the uncertainty in the calibration device used to evaluate U_{man}, based on a smile of devices.

The resolution of the measurement devices ($U_{\theta_{res}}$) is ±0.25K. 10 devices where placed with a reference device in a sealed chamber and exposed two sets of varying measurement ranges: 15℃ →17℃ and 21℃ →23℃ . The reference devices was a Hobo UA-001 calibrated ($U_{\theta_{cal}}$) to ±0.47K. The uncertainty in the variation in the sensors was been calculated based on the error between the calibrated instrument and the measurements made by each sensor,

$$S^2 = \frac{1}{n-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 , \qquad (2)$$

where S^2 is the variance, n is the number of sensors in the trial, N is the total number of measurements made (i.e. $N = nm$, where m is the number of measurements taken). The prediction intervals, where used to define $U_{\theta_{man}}$, since what is of interest is understanding what likely range *any* device would fall within, so that this value can be applied to other buildings using the same type of device. $U_{\theta_{man}}$ was calculated to be ±0.41K using a two-tail students t-statistic (t) at the 95% confidence level using,

$$U_{\theta_{man}} = tS\sqrt{1 + \frac{1}{n}}. \qquad (3)$$

Estimating $U_{\theta_{bulk}}$ requires more detailed measurements in a domestic property. What must be related is the air temperature measured at some high level (typically just above head height): to the bulk average in that space; or for the case of thermal comfort, to a location close to where such measurements are important (on the settee in the lounge, for example); or for control, i.e. estimate the conditions at a thermostat. A typical UK 3 bedroom, semi-detached house of 1930s construction was selected[1].

The room temperatures were surveyed on a regular grid at three heights (50mm, 1000mm and 2200mm from the floor), See Figure 1. The test was conducted in on evening in April 2012 starting at 17:30 and finishing 22:30. The external air temperatures at the beginning and end of the experiment were 11.8℃ and 11.3℃ respectively.

The house had not been heated since 08:00 when the test commenced and the first set of measurements were taken with then property in this state (17:30 to 18:30). The heating system was then switched on at 18:30 and left until the room temperatures were beginning to rise. A second round of measurements were taken between

[1]The floor area of the property is about 83m^{2}split over two storeys, with a floor to ceiling of 2.5m. The space comprise of a lounge, kitchen and hall downstairs and three bedrooms and bathroom and a landing upstairs. Construction is brick/cavity walls, post construction filled with insulation, vented loft space with 200mm of insulation and a suspended wooden floor ventilated with outside air. The back rooms have ben double glazed, while the front rooms and the hall and landing remain the original timber single glazed units. The suspended portion of the kitchen floor, has been insulated with 100mm of rock wool insulation. The heating is via a modern combiboiler and two-pipe radiator network, with at least one radiator in each room.

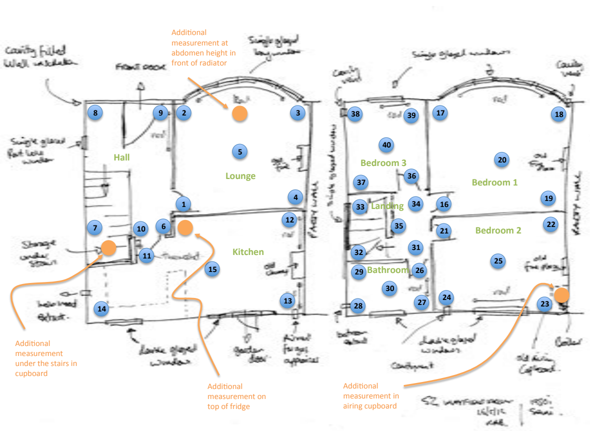

Figure 1: House plan and measurement points for the estimation of the uncertainty in the estimate of bulk average air temperature.

19:00 and 20:00. The system was then left for a time to let the internal environment approach the thermostat set point and hence be closer to steady-state. A third round of measurements followed between 21:30 and 22:30. These three tests were designed to establish the variation in room temperatures that can occur in three states:

- cold, heating system off,
- transient, while heating, and
- steady state heating on.

Assuming that each temperature in each room is representative of an equal volume of air, the best estimator of the bulk average air temperature, $\bar{\theta}_{bulk}$, is given by the mean of the measurements is given by,

$$\bar{\theta}_{bulk} = \frac{1}{n}\sum_{i=1}^{n}\theta_i. \tag{4}$$

where θ_i are the temperatures at each location. The prediction limits are calculated from the standard deviation, as given in Equation 3. The bulk average air temperatures and the prediction limits for each room for each of the three test cases is given in Table 1.

Given that the indoor outdoor temperature difference was between 6K when cold and 11K when heating, it might be expected that there is not a great deal of difference in the variation of the measurements across the heating modes. The variation in the kitchen and hall are greatest under heating and this is not surprising since there are both rectangular spaces with the radiator at on end and both are quite prone to drafts through poorly fitting external doors and vents. The lounge appears to be the coolest room under heating and this is likely since it has large single gazed bay windows. Bedroom 1 has the same windows and is also cooler than the other upstairs rooms.

For the purposes of estimating the uncertainty in the bulk average air temperature $U_{\theta_{bulk}}$ for general use in calculations the use of the mean uncertainty derived from the figures in Table 1 is proposed: ± 0.9K, although a slightly higher value might be expected when there is a greater temperature difference between inside and outside air temperature. When an estimate of thermal comfort is required, The air temperature in the abdominal plane (about 1000mm off the floor) is more important than one at high level in the room and hence a check was carried out to see if $U_{\theta_{bulk}}$= 0.9K was appropriate. Since comfort location in residential properties can be location specific (i.e. watching the TV on the sofa), it is important to consider the differences between all potential locations of the sensor at high level and all potential locations of the target temperature at abdomen level.

For each room, the difference from each high level temperature measurements to each abdominal level were calculated for each for the three cases. There were therefore 25 differences per room (16 in the hall and landing) totalling 546. The number of absolute differences exceeding 0.9K was 40, equivalent to 7%. At the 95% confidence level, this would indicate that the because the position in the room is critical for these applications (i.e. a sensor has a precise location, or someone is seated in a precise location), the uncertainty associated with the estimate of temperature at that location, given that the estimate can be generated from any of 5 locations in the room, is greater. If the uncertainty is raised to ± 1.1K the number of times this is exceeded falls to 5%. Hence when calculating bulk average temperature using a device mounted at high ($\approx$2.2m) level in one of the four corners of the room, the uncertainty is estimated at ± 0.9K, and when estimating the temperature at another location in the room, a value of ± 1.1K is more appropriate.

Electrical power

The measurement of electrical power consumption is made through the application of two devices, current transducers (CT) clips and an in-line plug in monitor, or smart plug (SP). The devices measure apparent power via the hall effect and convert the current measurement to power by assuming a voltage. The apparent power is given by $P_a = VI$, and the real power by, $P_r = P_a cos\phi$. The uncertainty in these measurements will be related to the assumption and actual variability of the supply voltage, the precision of the current measurement, and the estimation of ϕ. The Electricity supply regulations (SI 1994, No.3021) states that tab voltage tolerance 230V -6%, $+10\%$ (216.2V to 253V), due to be widened to 230 V $\pm 10\%$ (207 V to 253 V), hence a estimate of $U_v = \pm 23$V is considered to be reasonable when comparing power measurement from one property to another. When considering devices in the same home, the bias will (for practical purposes) be correlated. The uncertainty in the estimation of power factor has been taken to be $U_{phi} = \pm 0.1$, and where ϕ is not known $\phi = 0.9$ has been estimated as the mean for a number of devices (Rynone, 2007;

Table 1: Estimates of bulk average air temperature andprediction limits for each room.

θ_{ba} (℃)	**Lounge**	**Kitchen**	**Hall**	**Landing**	**Bath**	**Bed 1**	**Bed 2**	**Bed 3**
Cold	18.3	17.3	17.2	17.7	18.0	17.0	17.4	17.6
Transient	19.4	20.0	20.3	22.0	22.4	21.4	23.2	22.0
Heat SS	22.5	21.4	22.0	23.2	23.4	22.0	23.5	23.7

U_{ba} (℃)	**Lounge**	**Kitchen**	**Hall**	**Landing**	**Bath**	**Bed 1**	**Bed 2**	**Bed 3**
Cold	1.1	0.6	0.3	0.3	0.3	0.3	0.7	0.2
Transient	0.3	0.8	3.1	0.4	0.9	0.8	0.6	0.8
Heat SS	0.8	2.1	3.5	0.7	0.8	0.2	1.4	0.5

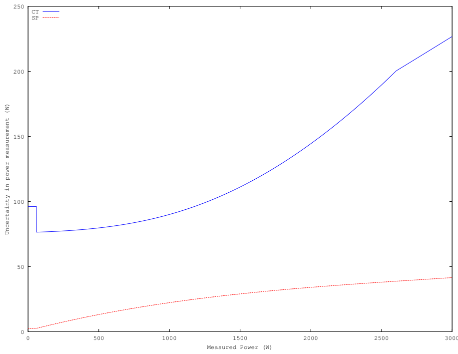

Figure 2: Uncertainty in CT and SP power measurement as a function of load (U_{man}).

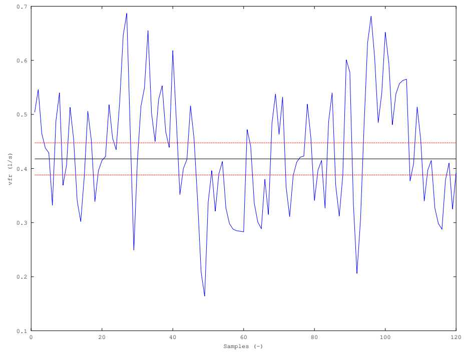

Figure 3: Uncertainty in gas flow rate conversion process (U_{conv}).

Paget et al., 2008; Farooq et al., 2011).

In addition, the device calibration and manufacturing variability (affecting the current measurement) will have an impact the uncertainty, in particular the low current characteristic behaviour. To evaluate this, a small number of CT and SP devices were subjected to varying loads (17W, 40W, 60W, 1.3kW, 2.6kW) to ascertain the reading error. The real power was measured by a Multicube digital power meter with an accuracy of $U_{cal} \pm 1\%$. It was found that the devices could not measure loads below 60W. The SP devices performed better and Figure 2 gives the resultant uncertainty in relation to the measured power, by both CT and SP devices (U_{man}). The uncertainty in a real power measurement is given by,

$$U_{P_r} = \sqrt{\sum_{i=1}^{n} \left(\frac{\partial P_r}{\partial i}\right)^2 U_i^2}, \qquad (5)$$

where i refers to ϕ, cal, man and v. Here, $U_v = 0\text{V}$ when the analysis considers devices that are fed by the same voltage supply and $U_v \neq 0\text{V}$ otherwise: the former case is considered for this paper. Note that the sensitivity coefficient $\frac{\partial P_r}{\partial i} \neq 1$ here because of the cosine term in $P_r = P_a cos\phi$.

Gas volumetric flow rate and calorific value

The uncertainty in the gas volumetric flow rate ($\dot{V}_{gas}$) will be affected by the precision of the measurement of the meter and the accuracy in the interpretation of the images of the meter. The uncertainty in the energy contained in the gas volume supplied will also be a function of the variation of calorific value of natural gas and the temperatures and pressures of the system. A pragmatic approach has been taken where,

$$U_{\dot{V}_{gas}} = \sqrt{U_{conv}^2 + U_{cal}^2}, \qquad (6)$$

where U_{conv} and U_{cal} are the uncertainties in the digital conversion process and in the meter calibration respectively. When calculating the energy conveyed ($U_{Q_{gas}}$), terms for the uncertainty in the calorific value, $U_{Cv_{gas}}$ and be added. $U_{cal} = \pm 3\%$ is taken from the statutory requirements for European meter accuracy and the $\bar{C}v_{gas} = 39.5\text{MJm}^{-3}$ and $U_{Cv_{gas}} = \pm 1.5\text{MJm}^{-3}$. U_{conv}^2 has been estimated here from a sample of gas data by estimating the 95% confidence limits over 1 minute (60 samples) of data. $U_{conv}^2 = \pm 0.03\text{ls}^{-1}$, and Figure 3 depicts the data, mean and confidence limits. At typical gas flow rates this equates to an error of $\pm 7\%$.

Water volumetric flow rate and temperature

The water flow rate is measured using a flow meter with an accuracy of $\pm 3\%$ of flow rate. The water temperature sensors measure within $\pm 0.5\text{K}$, however when used to estimate the water temperature they will also be affected by the ambient conditions since they are fixed to the outside of the copper pipe through which the water flows. Typical hot water flow temperatures from condensing boilers has ben observed to be in the region of 40℃ to 50℃, whereas tanked systems can be in the region of 50℃ to 60℃. Ambient conditions are between 18℃ and 25℃ and hence there will be bias in the measurement as a result of the installation, however, when the difference between the temperatures is used, i.e. for calculating heat flow ($Q_w = \dot{m}Cp_w\Delta\theta$) then these errors will be correlated and can be considered to be zero and,

$$U_{Q_w} = \sqrt{U_{\dot{m}_w}^2 + U_{Cp_w}^2}, \tag{7}$$

and often U_{Cp_w} can be considered to be negligible.

IMPACT ON ANALYSIS

Here are presented an number analyses, or calculations that may form part of a building energy study. Each problem is defined, the relevant calculation stared and the uncertainties applied. The implication of the uncertainties on the analysis are discussed for each.

Estimating hot water production efficiency

A modern condencing combi-boiler has a maximum output when heating for hot water, and so the efficiency in the production of hot water, η_w can be estimated using,

$$\eta_w = \dot{Q}_w/\dot{Q}_{in}, \tag{8}$$

where $\dot{Q}_{in}$ is the heat input to the boiler, which can be calculated from $\dot{Q}_{in} = \dot{V}_{gas}Cv_{gas}$. The uncertainty in the estimate of $\dot{Q}_{in}$ will be a function of $U_{\dot{m}_w}$, $U_{\dot{V}_{gas}}$ and $U_{Cv_{gas}}$. A further issue to consider is whether the efficacy of interest is the efficiency of the boiler under steady-state conditions, such as when running a bath or shower, or whether the over all average efficiency of hot water production throughout the day is of more interest, which is also likely to affect the uncertainty, since the operation of the boiler is more likely to be transient. Figure 4 details the data taken from H30 for a shower. The water flow rate is on the top plot, the temperatures of the water flowing into and out of the boiler in the middle plot and the gas flow rate on the bottom plot. The dashed horizontal line on the bottom plot is the mean flow rate calculated during steady-state conditions between the two vertical lines, repeated on each plot.

From the plot, $Q_w = 19.776$kW, ±0.59kW, the heat surrendered by the gas is $Q_{in} = 29.048$kW±2.21kW, and hence $\eta = 68\% \pm2\%$. In the calculation, the uncertainty contributions are 84.5%, 14.8% and 0.7% from the estimation of $\dot{V}_{gas}$, $\dot{m}_w$ and Cv_{gas} respectively. For this example, the stated hot water production efficiency is 84% hence even accounting for uncertainties in the measurements, the boiler appears to be operating with nearly 15% less efficiency that the manufacturer suggests.

Estimating ventilation rate

Here an estimation is made of the daily average ventilation rate using a sensible heat balance approach. The

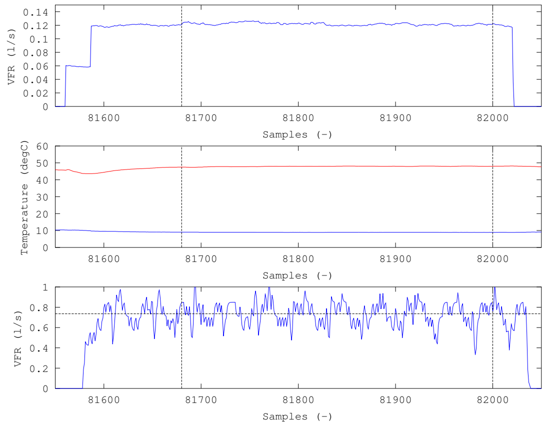

Figure 4: Steady-state hot water production efficiency data.

calculation applied here is based on a simple steady-state relationship based that assumes: the heat used through gas, accounting for the efficiency of the boiler is input into the space; the heat in the hot water all leaves the building (down the drain); the electrical power is converted to heat; the house is occupied; and heat is lost through the fabric and via ventilation.

$$Q_v = (Q_g + Q_e + Q_p) - (Q_w + Q_f), \tag{9}$$

where Q_v, Q_g, Q_e, Q_p, Q_v and Q_f are the daily sum of heat for ventilation, gas combustion, electricity consumption, gains from people hot water production and loss through the fabric, respectively, all in kW. Figure 5 shows 24 hours of data: gas heat flow, hot water heat flow, electrical power and indoor and outdoor temperatures. Table 2 gives the daily sums of the heat load values with the estimates of uncertainty and the resultant balance, used to estimate of Q_v. Q_f is estimated from the mean daily indoor and outdoor air temperatures (17℃ and 9℃ respectively) and an over all UA of 324W/K $\pm10\%$. There are 4 people occupying the house who emit 100W ±10W. Taking $Q_v = \frac{NV}{3}\Delta T$ where ΔT is the daily mean outdoor temperature, $N = 3.2\text{hr}^{-1} \pm0.29\text{hr}^{-1}$, which is a reasonable for a property of this type and age.

Table 2: Estimates of daily energy use totals.

Use	Quantity (MJ)	Uncertainty (MJ)
Q_g	281	±21
Q_e	68	±7
Q_p	35	±4
Q_w	29	±1
Q_f	224	±22
Q_v	131	±31

Identifying unmeasured electrical loads

A useful exercise when monitoring small power can be to check that the sum of the power measured at each circuit equals the power at the incoming mains conductor. Unmeasured loads occur where all circuits

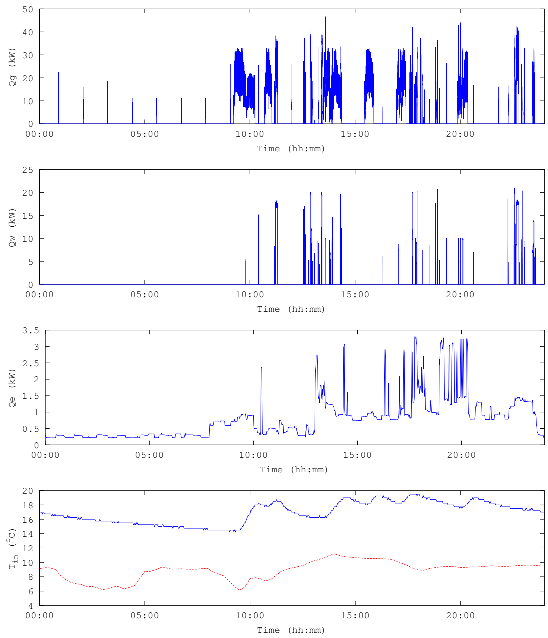

Figure 5: Heat balance data for H30.

cannot be measured, which is often the case due to expense, practical constrains due to the physical size, on the limiting factors such as a capacity ceiling on the monitoring equipment, it is useful to check whether there are any changes significant connected but unmeasured loads while monitoring. The top plot of Figure 6 depicts the daily power profile of H33, one of the homes in the study. The solid line is the power measured at the main incoming conductor, the dashed line is the sum of the power measured through most of the circuits. The bottom plot shows the dots which are difference between the sum of the circuits and the mains, the solid lines represent the uncertainty in the measurements. Power factor has been accounted for as has a known unmeasured load of a 160W freezer. The freezer in located in the garage, which is not monitored and when averaged represents a mean load; the cycling of the fridge causes the slight scattering above and below the zero line. Although the power factors have been estimated, this is a simplification and doesn't fully account for the observed differences and hence the deviations at 07:00 and 19:00 are largely caused by washing machine use. What this does show is the importance of assessing the uncertainty in these measurements to account for the simplifications.

Figure 7 This plot shows another day from H33 when the tumble dryer is used, which is also connected to garage circuit and is unmonitored, hence the difference between the sum-of-The application of uncertainty means that unmeasured loads in excess of $\approx$100W can be detected.

CONCLUSION

Uncertainty is an inevitable part of measurement and this is particularly evident data derived from inexpensive measurement devices in highly uncontrolled en-

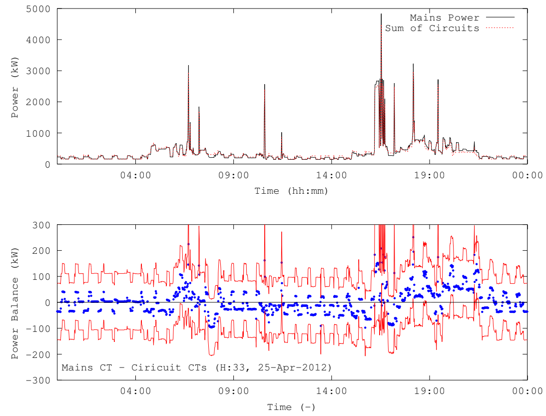

Figure 6: Balance of power between circuits and incoming mains conductor (H33).

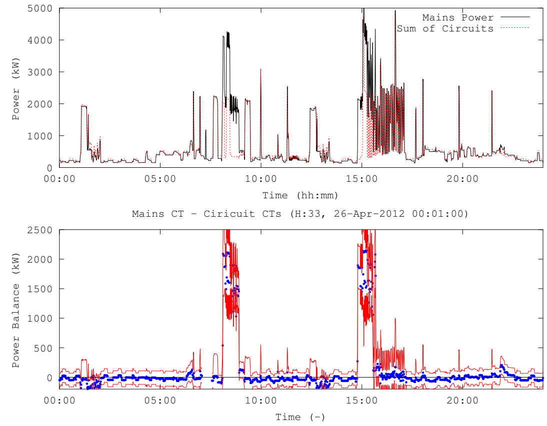

Figure 7: Balance of power in H33 with and unmeasured load (tumble dryer).

vironments such as residential buildings. This paper has presented a discussion on a pragmatic approach to evaluating these uncertainties for a range of typical whole house energy monitoring measurements and examples have been given to demonstrate of these might be applied to strengthen analysis, with two specific application areas in mind:

- **monitoring:** where the emphasis is on understanding why is happening which impacts targeting services, generating feedback and detecting changes in performance/consumption in condition monitoring type applications; and,
- **modelling and simulation:** when comparing simulated output with measurements, there are approximations in the model used and also uncertainties in the variables that are being estimated, both of which can have a significant impact on the interpretation of analysis.

ACKNOWLEDGEMENT

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REFERENCES

Breuker, M. S. and Braun, J. E. 1998. Evaluating the performance of a fault detection and diagnostic system for vapour compression equipment. *HVAC & R Research*, 4 No. 4.

Brohus, H., Heiselberg, P., Simonsen, A., and Srensen, K, C. 2009. Uncertainty of energy consumption assessment of domestic buildings. In *Proceedings of System Simulation in Buildings 2009*, Glasgow, Scotland.

Buswell, R, A. and Wright, J. 2004. Uncertainty in model based condition monitoring. *Building Services Engineering Research and Technology*, 25, number 1:65–75.

Buswell, R. A., Thomson, M., Webb, L. H., and Mirani, D. 2013. Determining heat use in residential buildings using high resolution gas and domestic hot water monitoring. In *Proceedings of System Simulation in Buildings 2013*, Chambery, France.

Coleman, H. W. and Steele, W. G. 1995. Engineering application of experimental uncertainty analysis. *American Institute of Aeronoutics and Astronautics*, 33, No. 10:1888.

Costola, D., Blocken, B., Ohba, M., and Hensen, J. L. M. 2010. Uncertainty in airflow rate calculations due to the use of surface-averaged pressure coefficients. *Energy and Buildings*, 42:881–888.

de Wit, S. and Augenbroe, G. 2002. Analysis of uncertainty in building design evaluations and its implications. *Energy and Buildings*, 34:951–958.

Domnguez-Munoza, F., Anderson, B., Cejudo-Lpeza, J, M., and Carrillo-Andrsa, A. 2010. Uncertainty in the thermal conductivity of insulation materials. *Energy and Buildings*, 42:2159–2168.

Farooq, H., Zhou, C., Allan, M., Farrag, M. F., Khan, R. A., and Junaid, M. 2011. Investigating the power quality of an electrical distribution system stressed by non-linear domestic appliances. In *In Proceedings of International Conference on Renewable Energies and Power Quiality*, Las Palmas, Spain.

Glass, A. S., Gruber, P., Roos, M., and Tödtli, J. 1994. Preliminary evaluation of a qualitative model-based fault detector for a central air-handling unit. In *Proceedings of 3rd IEEE Conference on Control Applications*, Glasgow, UK.

Kim, M., Yoon, H, H., Domanski, P, A., and Vance Payne, W. 2008. Design of a steady-state detector for fault detection and diagnosis of a residential air conditioner. *International Journal of Refrigeration*, 31:790–799.

Kline, S. J. and McClintock, F. A. 1953. Describing uncertainties in single-sample experiments. *Mechanical Engineering*, 75 No. 3:3.

Macdonald, I. and Strachan, P. 2001. Practical application of uncertainty analysis. *Energy and Buildings*, 33:219–227.

Paget, M. L., Lingard, R. D., and Myer, M. A. 2008. *Performance of halogen incandescent MR16 lamps and LED replacements*.

Rasouli, M., Ge, G., Simonson, C, J., and Besant, R, W. 2013. Uncertainties in energy and economic performance of hvac systems and energy recovery ventilators due to uncertainties in building and hvac parameters. *Applied Thermal Engineering*, 50:732–742.

Rynone, W. 2007. *Is Power Factor Correction Justified in the Home?*

Tian, W. and de Wilde, P. 2011. Uncertainty and sensitivity analysis of building performance using probabilistic climate projections: A uk case study. *Automation in Construction*, 20:1069–1109.