OPERATIONAL PERFORMANCE AND CALIBRATED MODEL ANALYSIS OF A LARGE LOW-ENERGY UNIVERSITY BUILDING

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ABSTRACT

This paper demonstrates a reproducible methodology for calibrating detailed energy models using hourly measured data that has been applied to evaluation of a large naturally ventilated university building. The aim of the project is to develop a rigorous calibration method and use it to investigate Energy Conservation Measures (ECM) and retrofit renewable energy technologies to achieve carbon emissions reduction. The methodology is based on a standardized day-typing method using data visualization and statistical techniques to establish accurate schedules for non weather-dependent demands. The influential weather-dependent sources of output uncertainty have been studied using two forms of sensitivity analysis. It was found that applying the Modified Morris method resulted in effective calibration with a manageable quantity of annual simulations and allowed some insight into the physical behaviour of the building. We also show how data visualisation has allowed further refinement of the model.

INTRODUCTION

Many organisations like Universities are seeking optimum means of improving the energy efficiency of their building stock and also evaluating investment in retrofit renewable technologies. Whole building energy simulation tools can play a valuable role in such analysis if satisfactory calibrated models with realistic sensitivities can be developed. There is, accordingly, a need for systematic methods for dealing with the uncertainties in the large sets of model parameters and inputs. At the same time, it is acknowledged that the total number and types of data source available for calibration purposes for a given project can vary significantly and so finding universal methodologies and evaluation criterial is difficult.

This paper presents details of a robust, systematic calibration methodology based on a step-wise evidence-based process that can be applied to large and complex naturally ventilated buildings with highly variable electricity demand profiles that are not weather dependent. Analysing hourly energy demand data sets allows derivation of representative operating schedules that can be used in the building model. This converts an inevitably stochastic system to a deterministic model allowing the methodic analysis of the building parameters without compromising the accuracy of the results. The selection of the input parameters is based on evidence-based data and sensitivity analysis and this assists the user to make decisions about those parameters where there is lack of strong evidence but avoid arbitrary modelling judgements.

The work reported here is part of a larger Living Lab project focussed on improving the performance of the Queens Building at De Montfort University (Figure 1). This iconic building is a good example of an advanced naturally ventilated building and received much attention on its opening in 1993 (Swenarton and Rickaby, 1993). The building is 10,000 m^2 in floor area spread over four storeys. The building incorporates two moderately large auditoria and a number of smaller classrooms on the ground floor. Much of the rest of the building is used for general purpose computing labs, engineering research labs and general office accommodation.

Figure 1: The Queens Building

Although the building was entirely naturally ventilated when constructed, it now incorporates a media technology facility which includes a teaching TV studio and associated production and editing facilities. The higher heat gains associated with these facilities have required some mechanical refrigeration systems to be installed. Energy data from the first years of operation showed better performance than contemporary buildings. Since then, as use has changed and as desktop computer use has expanded in both offices and many classrooms, electrical energy consumption has more than doubled. This has motivated the University to study this building in detail with a view to possible physical improvements or adoption of renewable technologies. The academic objective has been to try and do this in a technically rigorous manner and develop approaches that can be applied to many other buildings.

The building is supplied with grid electricity and natural gas for heating. As the refrigeration load is associated with zones with high internal gains that tend to be constant, and as the total refrigeration power demand is a small part of the whole, electricity use was not thought to be weather dependent. The building energy profile is characterised by a high base load but also some complex variations in daily peak loads over the year according to variations in teaching intensity and other changing usage.

THE CALIBRATION METHODOLOGY

The calibration methodology can be defined in terms of a stepwise process and is intended to be a reproducible approach suitable for non-domestic buildings with hourly energy data and weather independent electrical demands. We emphasise that this is an evidence-based approach and so surveying and on-site data collection is a fundamental element. The significant pre-modelling steps are day-type and baseload analysis. This is required in order to deduce model load densities, occupancy scheduling data and diversity factors. Simulation activities are guided firstly by sensitivity analysis with the aim of identifying certain model parameters that may be significant in final calibration and others that may be fixed. This requires definition of parameter ranges and a basecase. We examine two approaches to sensitivity analysis below. Parametric variation of selected sensitive parameters, data visualisation and model refinement are the final stages. The methodology is illustrated in Figure 2.

Building surveying and data collection

Developing the evidence-base for the modelling activity firstly entails establishing the applicable energy and weather data as well as basic geometric and construction data. The hourly energy consumption data sets and the hourly weather data over at least one year are essential for the calibration. The weather file should ideally be derived from a local weather station for the calibration period. The geometric and construction data may come from various sources but on-site surveying is valuable for verifying this information, establishing what HVAC systems are present but also observing the behaviour of occupants and effect of management policies. Hence it is valuable to carry out walk-through inspections of the building during daytime operation and at night.

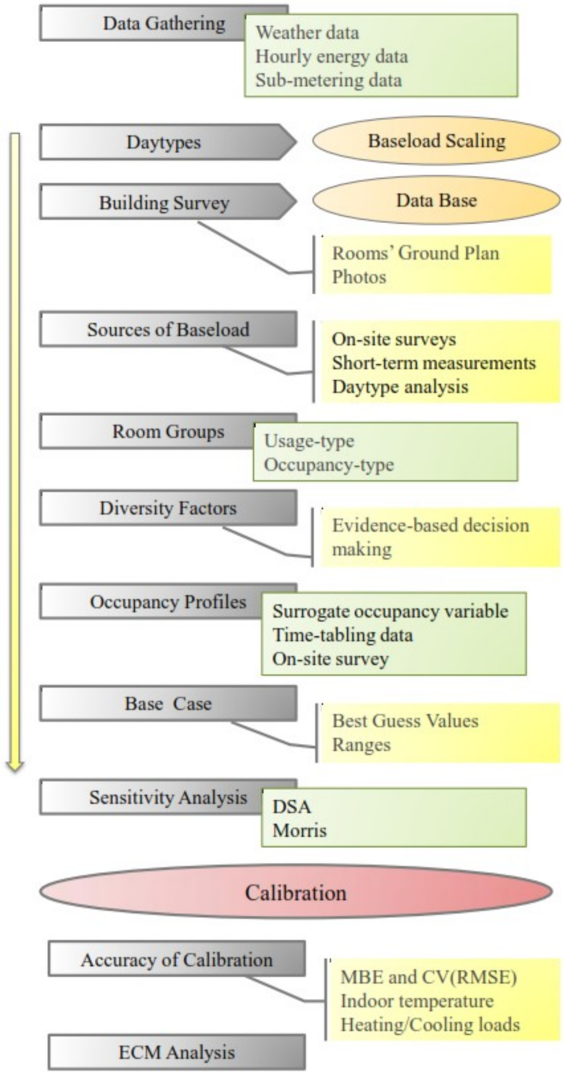

Figure 2: The calibration methodology

Room Data Sheets have often been used to capture the parameters affecting its performance such as occupancy levels, activity type, lighting power density, small power equipment etc. We have developed a graphical representation and data entry process to develop a database for modelling and data analysis purposes. This database can be a valuable tool for data archiving, classification, retrieval, analysis and potentially facility management. The technique is based on the open-source modelling and relational database tools SketchUp and MySQL. The tools are used in the surveying stage as follows:

Step 1 Define a Sketchup representation of each floor plan and zone.

Step 2 During the walk-through survey, encode room data sheets.

Step 3 Take record photos to verify the captured data and facilitate later reviews and derivation of missing information.

Step 4 Within SketchUp, attribute the room data using objects assigned to rooms in the drawing. Repeat steps 2–4 until the survey is complete.

Step 5 Transfer the data to a relational database (from SketchUp to MySQL) for later day-type analysis and model input preparation.

Data cleansing might be needed before the user can extract the data for model development and day-type analysis. Using data attributed to the graphical model of the floor plan allows convenient interrogation, progress monitoring and data quality control.

Day-type and baseload analysis

Day-typing is only applied to weather independent data sets and is the process used to create typical load schedules/profiles which will be used in inverse modelling techniques to attribute the measured electricity consumption to the model. Investigating the occupancy-driven (weather independent) parameters separately from the rest of the parameters simplifies the calibration process without compromising the accuracy of the model. A range of graphical and statistical techniques have been identified and combined to develop a robust process (Abushakra et al., 2001). The process we have adopted is defined in the following seven steps:

Step 1 Create time series graphs of the hourly monitored electricity data to identify and remove eroneous measurements.

Step 2 Investigate the weather dependency of the data sets using Box-Whisker-Mean (BWM) plots with ambient temperature as the binning variable.

Step 3 Provided there is no weather dependency, develop BWM plots using interquartile analysis (Abbas, 1993) and, in conjunction with the building operation calendar, identify general patterns (day groups).

Step 4 For each day group, examine the hourly and daily energy consumption graphs to reveal problematic data (e.g., outliers, drift, etc.)

Step 5 Develop the BWM plots with the x-axis showing the hour of the day and apply interquartile analysis on each bin. Day-types with same daily mean should be aggregated to obtain the primary day-types which undergo interquartile analysis again.

Step 6 For each day-type, compare the average daily consumption with the sum of the hourly values which have been calculated in step 5. If these are close enough then the profile is very representative of the actual energy use on a typical day, otherwise it is necessary to disaggregate the day-type and repeat the process.

Step 7 Develop annual schedules from the final day-types and evaluate by means of MBE and CV(RMSE) for the whole set of the typical and actual hourly data.

In the proposed methodology, derivation of day-types is followed by analysis of base loads. Insight into the base loads can form a useful element of energy demand reduction. We have also used this data to subsequently estimate occupancy variations. Base loads are analysed on the basis of day and nightime surveys and spot measurement of selected equipment. Base load due to the inattention of occupants to switching off lights and computers may be self evident in surveys. Less obvious sources may require further investigation. Base loads can be identified from each day-type schedule by the minimum load (e.g. at 1am). Subtracting the base loads from the total electrical schedules enables estimation of electrical loads correlated with occupancy. We have used the surrogate occupancy variable method suggested by Claridge and Abushakra (2001) that is a linear transformation of the lighting and equipment data excluding the baseload. In the case of educational buildings this data may be supported by timetable information and estimates of class sizes.

Sensitivity analysis

Once day-type analysis has established the non-weather related demands these can be used in the base-case model without further modification and attention can turn to weather related demands. In this type of naturally ventilated building, as there is no catering usage, this means studying the gas consumption associated with heating. Rather than take a black-box approach and vary all variables effecting heating demands, we suggest sensitivity analysis to eliminate parameters from the final parametric studies to be used in the final stages of calibration. Two common sensitivity methods for building energy simulation that we have applied are the Differential Sensitivity Analysis (DSA) method (Lomas and Eppel, 1992) and the Moris Method (Morris, 1991). These are briefly defined as follows.

DSA method. Each parameter is varied one at a time and the significance of its influence on the output is evaluated by the non-dimensional influence coefficient (IC) according to:

$$IC = \frac{\Delta OP/OP_{bc}}{\Delta IP/IP_{bc}} \tag{1}$$

where OP is output, IP is input and bc indicates base case values.

Morris Method. Each parameter varies one at a time but several times in the parametric space such that each factor is varied over the whole interval. The results are expressed by the value of the Elementary Effect (EE) according to:

$$EE = \frac{\Delta OP}{\Delta IP/(IP_{max} - IP_{min})} \tag{2}$$

The mean value of the effect (μ) of each parameter is then plotted against its standard deviation (σ) in order to identify the most influential factors (high μ) as well as the ones characterised by important interactions with other parameters (high σ) (Bertagnolio, 2012). Campolongo et al. (2007) introduced a revised version of the mean value (μ*) defined as the mean value of the absolute value of EE_i in order to avoid cancellation of differences of opposite sign.

Calibration criteria

The parameters identified as non-influential can be fixed to their basecase values, while the critical factors have to be redefined with further measurement if necessary. The model is considered sufficient calibrated when it fulfils the calibration objectives of the statistical indices of Mean Bias Error (MBE) and Coefficient of Variation of the Root Mean Square Error (CV(RMSE)). The maximum allowable values suggested in ASHRAE Guideline 14 (ASHRAE, 2002) are noted in Table 1 and have been applied in this work.

Table 1: Calibration criteria (ASHRAE, 2002)

Period	MBE (%)	CV(RMSE) (%)
Yearly	± 5	
Monthly	± 5	± 15
Hourly	± 10	± 30

MODEL DEVELOPMENT

Development of the model from the data available for the Queens Building is described in this section.

Gathered data

Hourly monitored electrical and gas consumption data was obtained for the years of 2008 to 2011. This data underwent quality control using graphical and statistical techniques. Two complete years of 2009 and 2010 were selected for use in the calibration process. This was partly because some conservation measures and other energy reduction initiatives were taken after 2010. Sub-metering is very limited in this particular building but such data was available over short periods for the refrigeration equipment. As this runs constantly to cool servers and media lab this data was assumed to be representative of operation over the year. Spot measurements were also made for some items thought to be contributing to base loads.
Hourly weather data was taken from a weather station installed on an adjacent building and processed into a simulation weather file. Quality control checks revealed short periods of corrupt and missing data. This was filled by: atmospheric pressure data from another nearby weather station; modelled dry bulb and humidity values, and; linearly interpolated solar data.
Geometric data for the model was not available in CAD form except for some floor plans made after a fire alarm survey some time after completion of the building. Other data was collected from site surveys. This geometry data was transferred to the IES-VE building simulation software. Very little information was available from manuals or the control system. Interviews of staff revealed ongoing winter thermal comfort and fault issues. For example, some ventilation actuators were known to be broken and many lighting PIR occupancy sensors were by-passed.

Day-type data

As a first step in the day-type analysis, the electrical consumption data-sets have been investigated for weather independency as illustrated in Figure 3.

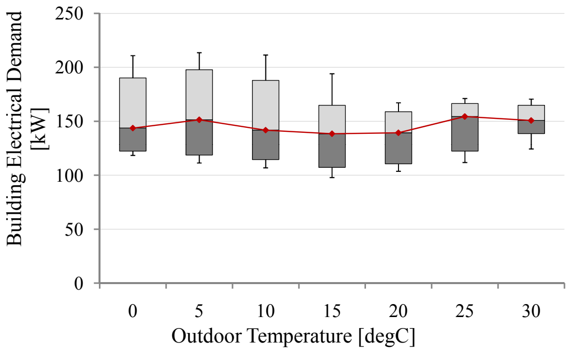

Figure 3: Hourly electrical consumption BWM plot with ambient temperature as the binning variable.

Considering the type of the building and its multifunctional character it is understandable that several day-types were identified (Table 2). These were verified by calculation of MBE (-1.76%) and CV(RMSE) (3.56%) when compared to the annual hourly data following the method described earlier.

Table 2: Derived day-types

No.	Period
1	Teaching period 1
2	Teaching period 2
3	Christmas/Easter/Bank Holidays for Stuff
4	Christmas/Easter Holidays for Students, Exams, Enrollment period
5	Weekends during the terms
6	Weekends during holidays
7	Summer

Baseload data analysis

The lowest base load was found to be approximately 100 kW and corresponds to the weekends during holiday periods (Figure 4). Although the base load during the weekends (day-types: 5,6) is greater by 12kW the profile patterns are very similar and indicate low occupancy during the second half of the day (Figure 5). During Christmas holidays there is an identifiable electrical demand of around 11kW from 6am to 8pm, and this was assumed to correspond to the heating system pump demand.

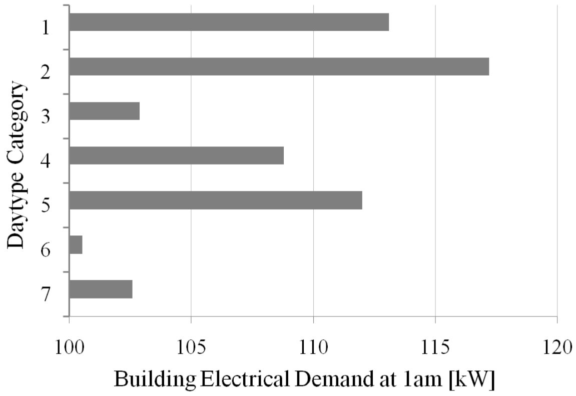

Figure 4: Base load electrical demand at 1am for each day-type.

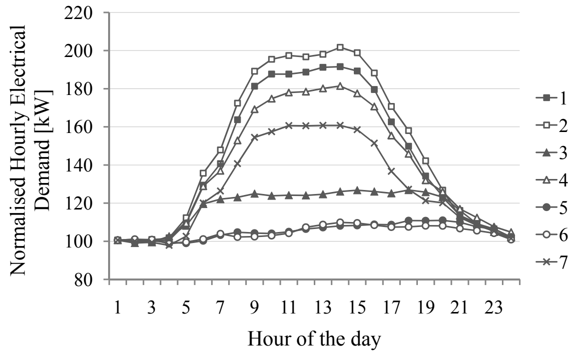

Figure 5: Normalised hourly electrical demand for each day-type.

Occupancy schedules were subsequently derived using the surrogate variable approach noted above (Claridge and Abushakra, 2001). Having completed the surveys, some estimate of the breakdown of the base loads could be made (Table 3). Approximately 80% can be justified directly, while the rest is allocated to the sources based on survey observations.

Table 3: Baseload sources

#	Baseload sources
1	Lighting
2	Plug Loads
3	Computers
4	Servers
5	Routers
6	Circulation pumps
7	Electric Hot water
8	Cooling
9	Refrigerators
10	Pumps in a nanotechnology laboratory
11	Auxiliary energy from BMS system

Although lighting and equipment densities were recorded for every room, it was more efficient in terms of model data entry, to group rooms according to similar levels of gain and type of occupancy. This resulted in 24 groups for equipment and lighting levels and 11 types of occupancy. Diversity factors were applied to the installed lighting loads and observed equipment power densities for each group to achieve equivalence with the day-type schedules and measured data. Some exceptions had to be made in this process as some processes are performed occasionally. For example, there is a Faraday cage lab which is used occasionally and so the energy demand cannot be proportional to the load density.

The nominal values of other input parameters (e.g. U-values) were chosen based on the collected data or benchmarks when there was no evidence. For example, there were no measurements for the infiltration rates and standard values for leaky buildings (Gowri et al., 2009) were initially used. The sensitivity analysis would reveal their influence and suggest subsequent refinement.

MODEL CALIBRATION RESULTS

Weather independent data

The modelled electrical demands correspond, as expected, to the typical schedules created following the day-typing process. The accuracy of the model demands with respect to the measured hourly data depends on the fidelity of the scheduled data. This has been evaluated and verified (MBE = 0.03%, $CV(RMSE)_{monthly}$ = 4.98%, $CV(RMSE)_{hourly}$ = 1.34%) during the model development. Figure 6 illustrates how well the hourly model data represents the meter data over the year.

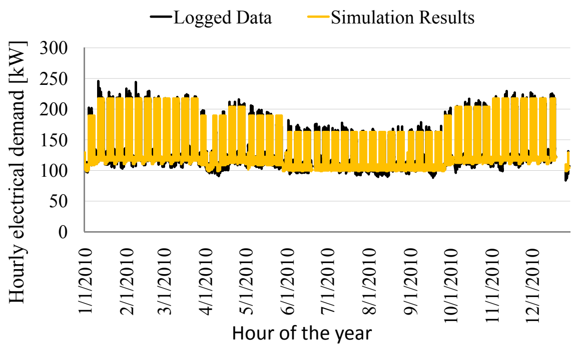

Figure 6: Measured and predicted hourly electrical demand (kW).

Weather dependent data

The basecase model did not satisfy the calibration criteria (MBE = -14.51%, $CV(RMSE)_{monthly}$ = 18.10%, $CV(RMSE)_{hourly}$ = 30.07%) for the gas consumption and data visualisation revealed certain periods of the year with high error (e.g. the second half of March as presented in Figure 7, corresponding to the Easter holidays). Sensitivity analysis was subsequently performed. The parameters selected for the sensitivity analysis were those thought, from consideration of the physical processes and model properties, most likely to influence heating demands (Table 4).

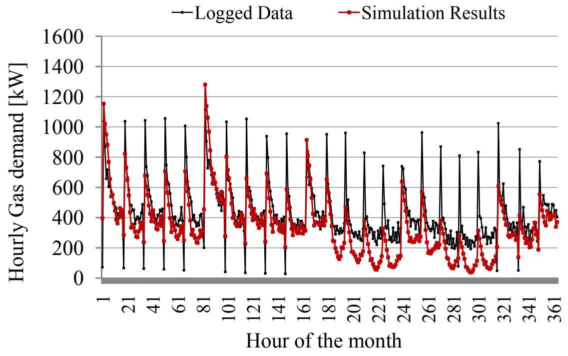

Figure 7: Measured and predicted hourly electrical demand (kW) for the month of March.

Table 4: Parameters considered in the sensitivity analysis

#	Variable	Description	Units
1	ACH_{inf}	Infiltration Rate	ACH
2	$T_{i.s.p.}$	Heating Set Point	degC
3	$n_{eff.}$	Heating system efficiency	-
4	U_{walls}	Walls U-Value multiplication factor	-
5	$U_{gl.}$	Glazing U-Value	-
6	$f_{occ.}$	Occupancy density multiplication factor	-
7	$f_{l.}$	Lighting density multiplication factor	-
8	$f_{comp.}$	Computers density multiplication factor	-

The sensitivity analysis results using the DSA method are plotted in Figure 8. The most influential parameters appear to be the infiltration rates and the heating system efficiency. The building model also seems to be sensitive to the lighting density and the wall properties. The heating set point temperature is also significant but less so the glazing properties, internal gain densities or occupancy.

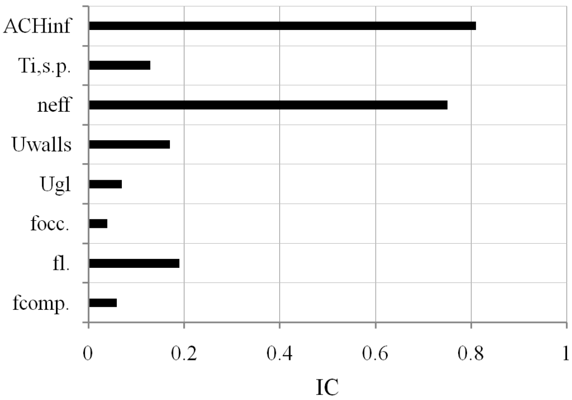

Figure 8: DSA sensitivity analysis results

Figure 9 presents the sensitivity analysis provided by the Morris Method. The ranking of influential parameters is broadly similar to those suggested by the DSA method. The infiltration rate remains the most influential parameter along with heating system efficiency and set-point temperature. The internal gain densities furthermore have imperceptible impact on the predicted gas consumption. However, the ranking of the significance of lighting density and the wall U-Value are reversed. Furthermore, this ranking was observed to be sensitive to the parameter range specified. The wall U-value was of significance when using the parameter range 0.42–0.60 W/(m^{2}K) but not significant if the range was 0.06–0.24 W/(m^{2}K). Direct comparison of the set-point temperature sensitivity is problematic using the DSA method as the temperature can't be non-dimensionalized to form a meaningful Influence Coefficient (Bertagnolio, 2012).

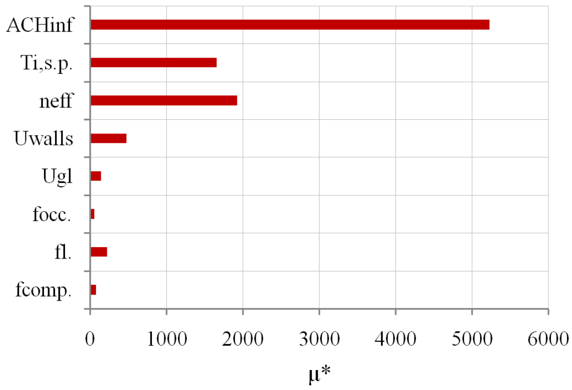

Figure 9: Morris method sensitivity analysis results

The Morris method can also reveal interactions and non-linearity. Viewing the (σ - μ) plane (Figure 10) gives an indication of the relationship between parameters. The most significant parameters (high value of σ) have a linear impact on the gas consumption, since they are located outside the lines defined by: $\mu = \pm 2 * \sigma/\sqrt{r}$ (the impact is considered as non-linear when the point is placed inside the lines). It is also of interest to examine the (μ - μ *) plane (Figure 11) which indicates that all the parameters are characterised by monotonic behaviour since their values of μ and μ * are the same.

Model refinement

Following the sensitivity analysis, three further stages of review and model refinement were undertaken. The calibration improvement at each stage is indicated in Table 6. In view of the sensitivity analysis results, glazing properties and wall U-values were reset to their basecase values that were based on available design data. There was little reliable evidence to arrive at an improved value of set-point temperature. Spot checks in 2012 suggested values of 22 °C but energy management staff expected lower values and also the control system was known to be unreliable and in need of recommissioning in the 2009–2010 calibration period. Varying the set-point temperature suggests the higher value is more representative (Table 5).

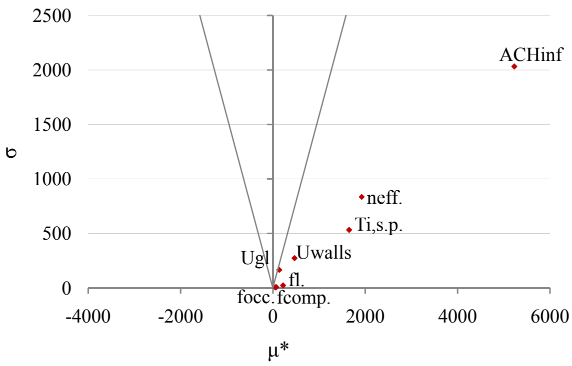

Figure 10: Morris sensitivity analysis - (σ-μ) plane.*

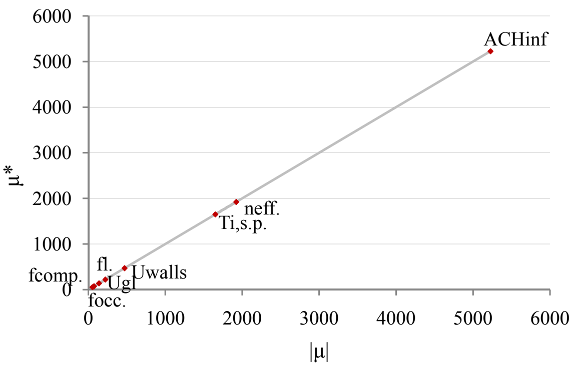

*Figure 11: Morris sensitivity analysis - (μ-μ *) plane.*

There was also a lack of evidence for the heating system efficiency. Using the best estimate of the boiler efficiency resulted in noticable underestimation of the gas consumption. Other factors (distribution losses and poor part load efficiency) may account for better results with lower values (0.65-0.75 overall efficiency). Further refinement followed fixing the efficiency at 0.70 and examining other deviations from the measured data. Simple data visualisation was found useful to examine the variations between day-types related to infiltration. The schedules used to represent infiltration were subsequently improved.

Visualization of the results also revealed gas consumption was overestimated on Mondays more than other days. Considering the cooling of the building during the weekends and the very high thermal mass of the fabric, it was thought that the set-point might not have been achieved due to the limited capacity of the heating system (also evident from records of occupant complaints on Mondays). The basecase heating system model had unlimited heating capacity. Limiting the capacity significantly improved the trend for Monday gas demands but only the hourly statistical metrics were noticeably improved. Table 6 presents the changes in calibration metrics at each stage of the model review and refinement along with the number of iterations used at each stage.

Table 5: Heating set-point sensitivity

	set-point temperature	
	21 °C	22°C
MBE	-23.92	-14.51
$CV(RMSE)_{monthly}$	27.01	18.10
$CV(RMSE)_{hourly}$	35.73	29.97

DISCUSSION

During the first review (third iteration), although the model met the monthly calibration criteria (MBE = 4.65% and $CV(RMSE)_{monthly}$ = 9.87%) the high hourly CV(RMSE) of 45.61% clearly indicated that some elements of the model were too unrealistic. This seems unacceptable if ECMs are to be evaluated as model sensitivities may not be realistic. Hence, more detailed evaluation using hourly data seems essential.
Moreover, although the model met both the monthly and hourly acceptance criteria at the completion of the second review, non-negligible errors remained (e.g. overestimation of gas consumption on Mondays) which was only revealed after vizualisation of the hourly trends. Statistical acceptance criteria take no account of time dependent behaviour or trends and so, in themselves, offer no insight into the reasonableness of the representation of the building physical processes in the model. Consequently, it is recommended that the calibration process is continued through more detailed examination of short timescale trends. In this case hourly gas consumption trends were helpful but we expect hourly indoor temperature data would have been of further value.
The two sensitivity analysis methods applied in this work were found to be in broad agreement but there are some differences in utility that are worth noting. The DSA method is characterised by (Campolongo et al., 2007) lower computational cost, simplicity of the sampling design and allows for deriving individual sensitivities and separately assessing the effects of the parameters. However, it does not explore the parametric space in a satisfying way and it cannot detect the non-linearities and interactions of the parameters. Furthermore, the direct comparison of all parameters, such as those involving temperature, is not feasible.
The Morris method allows the direct comparison of the parameters and these can be distinguished seamlessly in terms of linearity and monotonic behaviour. Moreover, several parameters—with values spread over the whole parametric space—can be examined with a relatively limited amount of simulation runs. The greater utility of the Morris method may consequently justify the additional effort required in developing the sampling design.
Special care was required in selecting parameter value ranges as results were found to be partly dependent on the range selected. This suggests testing different

Table 6: Statistical calibration indices achieved in each revision of the model.

Stage of calibration process	**Variations**	**MBE**	**CV(RMSE)$_{month}$**	**CV(RMSE)$_{hour}$**
Base Case.	1	-14.51	18.10	30.97
Identification of daily infiltration schedules (e.g. day-night).	2	0.5	4.53	26.07
Identification of infiltration day-types and investigation of the corresponding infiltration rates.	5	-2.07	5.85	25.83
Investigation of peak heating capacity.	2	-2.87	5.80	22.61

ranges may be worthwhile. It also suggests that the sensitivity analysis should be mainly relied on to establish the ranking of the parameter sensitivities and that calibration values be decided after further review and data vizualisation.

Although the identification and assessment of ECMs is out of the scope of this paper, the sensitivity analysis can clearly inform their selection. For example, improving heating system efficiency (boiler replacement) seems more effective than measures to improve U-values (e.g. window upgrades). Improved lighting could also be a significant measure.

CONCLUSIONS

An evidenced-based model calibration methodology has been demonstrated that should be applicable to a range of naturally ventilated building types with weather independent electricity demands. We conclude the following.

- Systematic derivation of day-types avoids arbitrary assignment of model parameters and schedules. It allows some parameters to be fixed accurately and eliminated from further parametric variations.
- Using day-typing methods is also useful for the analysis of base loads—an important factor in the energy consumption of public buildings.
- When the reliable data sources are exhausted, sensitivity analysis allows reduction of the parameter space and can minimise the need for additional measurements.
- Satisfactory calibration also relies on final stage data visualisation and hourly trend analysis to refine the representation of the building physical processes and improve the calibration metrics.
- Day-typing and sensitivity analysis are also useful in preliminary assessment of potential ECMs.

An in-depth analysis of ECMs and renewable technologies and the development of a systematic decision making methodology which integrates energy saving, emissions and economic analysis will be the objective of future work.

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