

## CALIBRATION OF WHOLE BUILDING ENERGY SIMULATION MODELS: DETAILED CASE STUDY OF A NATURALLY VENTILATED BUILDING USING HOURLY MEASURED DATA

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### ABSTRACT

This paper describes the calibration of a detailed whole-building energy simulation model of a naturally ventilated building to hourly measured data. This demonstrates the application of an evidence-based analytical optimisation approach described in a previous paper (Coakley et al. 2011). The methodology is applied to the following case study, naturally-ventilated library building at the National University of Ireland, Galway.

The simulation model is calibrated to measured building data for electrical energy consumption and zone temperatures. This is achieved by assigning probability distribution functions to continuous model parameters, generating simulation trials based on random sampling of these distributions and ranking solutions based on a calculated goodness-of-fit. The paper concludes with a discussion of the key findings of this study and future work.

### INTRODUCTION

#### **Background**

Whole Building Energy Simulation (BES) models play a significant role in the design and optimisation of buildings. Simulation models may be used to compare the cost-effectiveness of Energy-Conservation Measures (ECMs) in the design stage as well as assessing various performance optimisation measures during the operational stage.

However, due to the complexity of the built environment and prevalence of large numbers of independent interacting variables, it is often difficult to achieve an accurate representation of real-world building operation. Therefore, by reconciling model outputs with measured data, we can achieve more accurate and reliable results.

A novel calibration methodology has been developed based on a combination of evidence-based BES model development (Raftery, Keane, and O'Donnell 2011) and an analytical optimisation approach (Jian Sun and Reddy 2006). This paper demonstrates the application of this methodology to a naturally ventilated building. According to an extensive literature review, calibration of such a naturally

ventilated building model has not been conducted to date.

#### **Building Description**

The Nursing Library is a newly constructed building at the National University of Ireland, Galway located in Galway, Ireland. It has a gross floor area of 700m<sup>2</sup> and was completed in 2009.



*Figure 1: NUI, Galway Nursing Library*

The 3-storey building contains a library and study areas, as well as a computer room on the ground floor. It operates from 8:30am to 10pm on weekdays and 9am to 5pm on Saturdays/Sundays.

#### **HVAC Systems**

The building has a mixed-mode ventilation system with a dedicated outside air system (DOAS) for forced ventilation and automatically (or manually) operated windows for natural ventilation in most areas. The DOAS draws air through an earth tube system to temper the air in the winter and summer months. Stand-alone direct exchange units cool the computer rooms. Convective hot water baseboard heaters maintain indoor temperatures outside of the summer months. Campus-wide district hot water supplies all of the heating systems in the building.

#### **Stock Information and Measured Data**

The quality of stock information about the building is very high due to its recent construction. High quality as-built drawings and detailed information on materials and constructions are available. In addition, Operation and Maintenance (O&M) information and

detailed design criteria is available for all the HVAC equipment.

The existing Building Management System (BMS) already monitors:

- Space temperature (°C)
- Space CO<sub>2</sub> levels (ppm)
- Electrical Energy Consumption (kWh)
- Heat Energy Consumption (kWh)

The electrical layout also explicitly separates electricity consumption by end-use, such as lighting, plug loads and HVAC systems.

## METHODOLOGY

A previously published paper (Coakley et al. 2011) describes the calibration methodology in detail. The process may be broken down into five main steps (Refer to Figure 2):

1. Data gathering / building audit.
2. Evidence-based BES model development.
3. Bounded grid search
4. Refined grid search (optional)
5. Uncertainty analysis

In order to avoid an over-reliance on analyst knowledge and judgement, this methodology follows a clear evidence-based structure and proven statistical methods.

## Version Control

The entire process is tracked using version control software (TortoiseSVN Core Development Team 2011) to improve the reproducibility and reliability of the results.

## Data Handling

Since the calibration process requires the collection and archiving of large amounts of data, it was decided at an early stage that a Relational Database Management System (RDBMS) would be used for storing and accessing this information.

## STAGE 1: DATA GATHERING

While the primary focus of this study is the simulation and calibration of BES models, a significant effort was also devoted to collecting, archiving and processing the data required for this purpose.

### (i) Building Description Data

The first step was to obtain comprehensive data pertaining to the building and its systems. This information was sourced from:

- As-built drawings
- Operation & Maintenance (O&M) manuals
- Building surveys
- Interviews with facilities manager

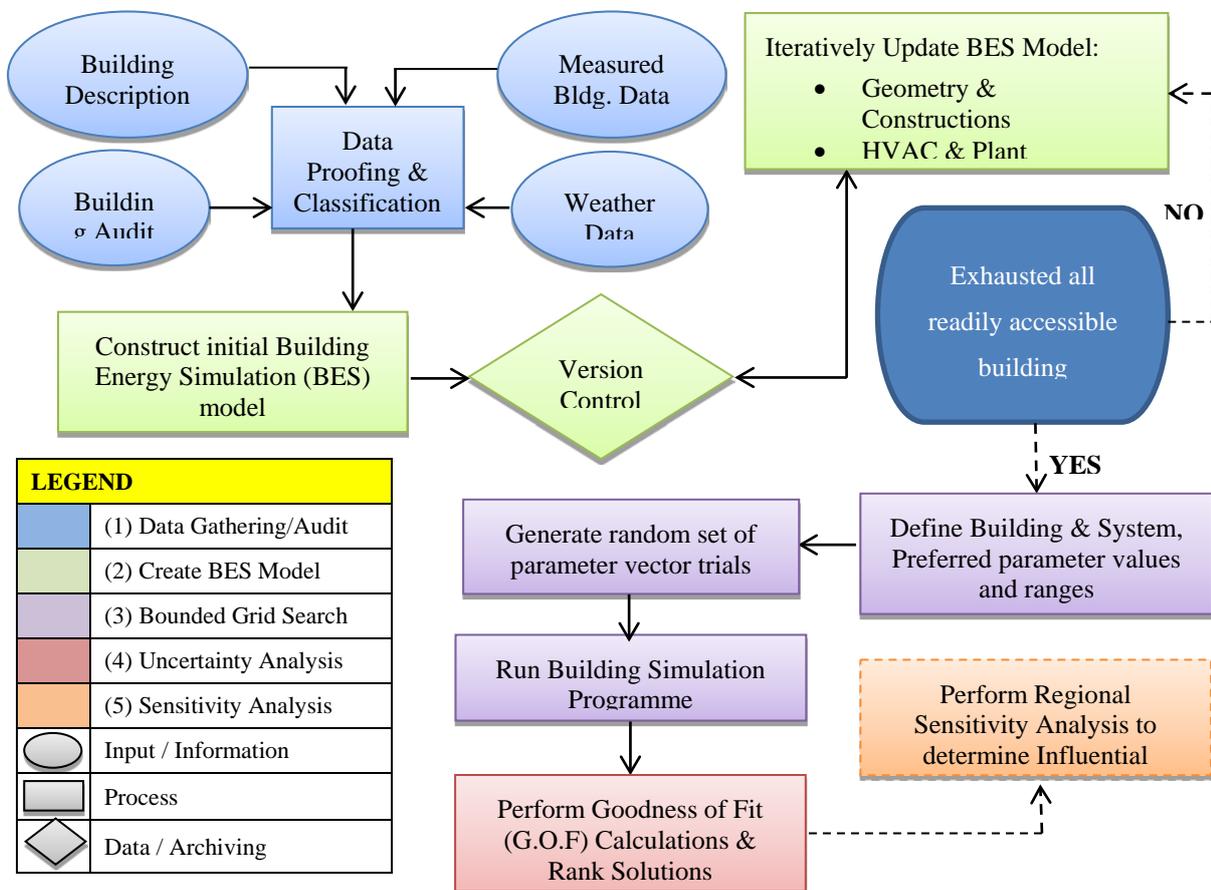


Figure 2: Overview of Calibration Methodology

### **(ii) Measured Building Data**

As previously mentioned, the BMS already measured a number of parameters including space temperatures, CO<sub>2</sub> levels, electrical energy consumption and heat energy consumption. However this data was only monitored and not recorded on a long-term basis. The facilities manager was consulted and data archiving was implemented in April 2011. Unfortunately, a failure in the BMS reporting system resulted in the loss of 5 weeks data from 21<sup>st</sup> December 2011. This issue has now been resolved and data archiving has been restored.

Temperature sensors were also installed on the low-pressure hot-water (LPHW) System at the supply and return side to verify heat meter readings on the BMS.

### **(iii) Weather Data**

In order to accurately simulate the building response to external conditions, it was necessary to gather detailed weather data for the full simulation period. For this purpose, a weather station was installed on campus measuring:

- Dry-bulb temperature ( $\pm 0.5^{\circ}\text{C}$ );
- Relative humidity ( $\pm 2\%$ );
- Barometric pressure ( $\pm 50\text{Pa}$ );
- Wind speed [ $\pm 0.1\text{ms}^{-1}$  ( $0.3 - 10\text{ms}^{-1}$ );  $\pm 1\%$  ( $10 - 55\text{ms}^{-1}$ );  $\pm 2\%$  ( $> 55\text{ms}^{-1}$ )];
- Wind speed -3s gust [ $(\pm 0.1\text{ms}^{-1}$  ( $0.3 - 10\text{ms}^{-1}$ );  $\pm 1\%$  ( $10 - 55\text{ms}^{-1}$ );  $\pm 2\%$  ( $> 55\text{ms}^{-1}$ )];
- Wind direction [ $\pm 2\%$  ( $> 5\text{ms}^{-1}$ )];
- Global solar irradiance ( $< 5\%$ );
- Diffuse solar radiation ( $< 15\%$ );
- Barometric pressure ( $\pm 50\text{Pa}$ );

This data is recorded and stored on a remote server in .dat format. A batch process is used to access this server and download the weather file on a weekly basis.

### **(iv) Building Audits**

Building Audits were carried out to obtain additional information for the following:

**Electrical Equipment:** An equipment survey was carried out in March 2011. All electrical equipment in the building, including computers, printers, televisions etc., was listed along with their rated power consumption (W).

A three-phase power supply splits electrical loads in the building under the following end-use categories:

- Lighting
- Power (AC Units, cameras, spurs)
- General Services (Plug sockets)
- Sub-Distribution (MCC, elevator, fire alarm)

A detailed electrical audit was conducted in September and December 2011 using a 3-phase electrical meter

**Lighting:** A lighting audit was carried out in March 2011. The building is fitted with standard 5ft 56W T12 fluorescent tubes combined with CFL bulbs in hallways and stairwells.

**Occupancy:** Occupancy surveys are carried out at random times over the course of a week during selected periods of interest throughout the year:

- Regular term time – Semester 1
- Regular term time – Semester 1
- Pre-exam period
- Summer period

In addition, data pertaining to PC usage (Log-on times and usage period) in the building is collected on a continuous basis on the campus-wide Labstats software. This provides a valuable input for determining occupancy profiles and electrical equipment usage schedules.

### **Data Proofing and Classification**

Before we can compare our measured and simulated data, it is first necessary to proof the data and perform any necessary pre-processing steps.

Measured data commonly contains one or more of the following deficiencies, such as: unnecessary fields, inconsistent data, missing time periods, and, missing information.

As a general rule, where data is missing or incorrect for short time-periods ( $< 6$  hours), we used simple interpolation to generate missing values. Where long-term data is missing, these periods were excluded from final goodness-of-fit (GOF) calculations

### **(i) Weather Data**

In their raw format, the weather data files are unsuitable for direct input into EnergyPlus. Much of this pre-processing is handled using MySQL where unnecessary fields are removed from and checks are performed for inconsistent values. Once complete, the file is then passed to EnergyPlus Weather Converter for conversion to EnergyPlus Weather (EPW) format. This software uses input data to compute missing values for:

- Dew Point Temperature ( $^{\circ}\text{C}$ ),
- Direct Normal Radiation ( $\text{Wh}/\text{m}^2$ ),
- Illuminance (lux)
- Sky Cover

### **(ii) Building Management System (BMS) Data**

BMS Data is recorded daily on a remote BMS server archive. Each individual sensor data point is stored in a separate comma-separated value (.csv) file with a unique identifier. Data is recorded using the following format:

$$\begin{array}{l}
T_{1,j}, u_{1,1}, u_{1,2}, \dots, u_{1,j} \\
T_{2,j}, u_{2,1}, u_{2,2}, \dots, u_{2,j} \\
\dots \\
T_{i,j}, u_{i,1}, u_{i,2}, \dots, u_{i,j}
\end{array}$$

Where:

- $T_i$ , Timestamp at row  $i$ , interval 1;
- $j$ , Number of samples = 1024;
- $u_{i,j}$ , Sensor value at row  $i$ , interval  $j$ ;

With over 60 individual sensors for this building recording 1024 values daily to separate csv files, this resulted in approximately 22 million data points with around 90% of this information duplicated due to overlapping time periods. A program was written for initial pre-processing and loading this data in our MySQL database.

### STAGE 2: INITIAL BES MODEL DEVELOPMENT

This information collected in Stage 1 was used to construct our initial single-zone BES model using the OpenStudio plug-in for Google SketchUp.

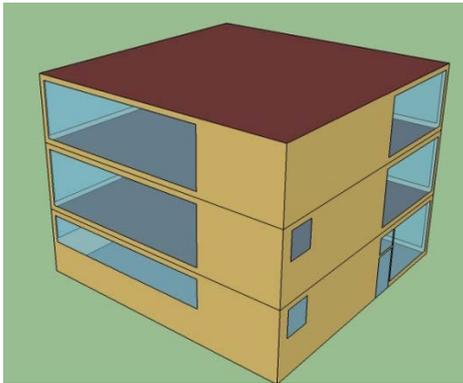


Figure 3: SketchUp Model

Zone information and HVAC details were added to the model using HVACGenerator (Raftery et al. 2012). This tool outputs macro-format simulation files compatible with EnergyPlus V7.0.

### Iterative Model Development

The BES model was iteratively updated to reflect new information collected during continuous data gathering. Each revision was tracked and linked to source information using version control software.

A detailed list of model inputs is also maintained for the purpose of Parametric Analysis. A sample of 10 of these parameters can be found in Table 2.

The parametric analysis evidence sheet provides a complete list of every object in our EnergyPlus model, grouped according to EnergyPlus Input/Out Reference Class. Each field value is recorded in this sheet and linked to source evidence. A drop-down menu allows the user to select the class of source evidence based on a hierarchy of reliability as illustrated in Table 1.

### STAGE 3: DEFINE RANGES OF VARIATION

Each class of source evidence outlined above has an associated ranking and range of variation (ROV, %). This ROV represents the total heuristically estimated deviation from the mean value. These are currently preliminary estimations based on prior experience and may change throughout the course of the study.

Table 1: Hierarchy of Source Evidence

| SOURCE                   | CLASS | ROV (%) |
|--------------------------|-------|---------|
| BMS Data                 | 1     | 0       |
| Sensor Data              | 1     | 0       |
| Spot-Measured Data       | 2     | 5       |
| Physically Verified Data | 2     | 5       |
| As-Built Drawings        | 3     | 10      |
| O&M Manuals              | 3     | 10      |
| Commissioning Documents  | 3     | 10      |
| Design Documents         | 4     | 15      |
| Guides & Standards       | 5     | 30      |
| Default Values           | 6     | 40      |
| No Available Information | 7     | 50      |

Using the above ranges of variation, probability density functions (PDFs) were developed, based on normal distribution  $N(0, \sigma^2)$ , for each of our continuous input parameters. For example, the probability density function for insulation conductivity (Figure 4) was calculated as follows.

$$\sigma = \frac{u * ROV}{3}$$

Where:

- $\sigma$ , Standard Deviation;
- $u$ , Initial Value;
- $ROV$ , Range of Variation;

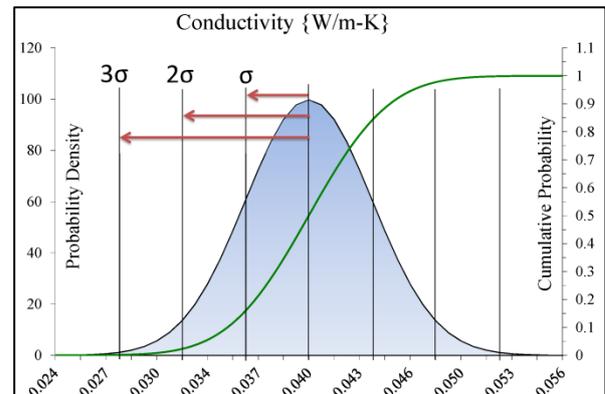


Figure 4: PDF for Insulation Conductivity Value

These probability density functions (pdf) are used to generate random simulation trials. It should be noted that we are just sampling a small fraction of input parameters at this stage to illustrate the process involved.

Table 2: Sample from Parametric Analysis Evidence Sheet

| OBJECT                  | FIELD                     | INITIAL VALUE | FURTHER INFORMATION   | CLASS | ROV (%) | STD DEV |
|-------------------------|---------------------------|---------------|---|-------|---------|---------|
| Schedule:Compact        | Field 3                   | 145           | EnergyPlus I/O Reference  | 6     | 40      | 19.33   |
| Material 1 - Insulation | Conductivity {W/m-K}      | 0.04          | Approved Document L1 Conservation of fuel and power in dwellings (2002) | 5     | 30      | 0.004   |
| Material 1 - Insulation | Specific Heat {J/kg-K}    | 1450          | BS EN 12524   | 5     | 30      | 145     |
| Material 2 - Concrete   | Conductivity {W/m-K}      | 2.5           | BS EN 12524   | 5     | 30      | 1       |
| Material 2 - Concrete   | Specific Heat {J/kg-K}    | 1000          | BS EN 12524   | 5     | 30      | 100     |
| WindowMaterial:Glazing  | Thickness (m)             | 0.003         | Drawings / 0517-GEA-001   | 3     | 10      | 0.0001  |
| WindowMaterial:Glazing  | Conductivity {W/m-K}      | 0.9           | Default Value   | 6     | 40      | 0.12    |
| Lights                  | Lighting Level {W}        | 13100         | Lighting Audit 03/03/2011   | 2     | 5       | 3000    |
| ElectricEquipment       | Watts per Zone Floor Area | 7             | Electrical Audit 04/03/2011   | 2     | 5       | 2       |
| Fan:VariableVolume      | Fan Efficiency            | 0.74          | Mechanical O&M Manual   | 3     | 10      | 0.05    |

### Generate Random Simulation Trials

For the purpose of our initial trial, the mean values and standard deviations for 10 independent parameters were specified. Using a random sampling algorithm based on normally distributed values, a set of 100 simulation trials were generated using R-Script.

### Run Building Energy Simulation Program

For the purpose of this research, we used jEplus v1.3 (Y. Zhang 2009) for conducting parametric analyses using EnergyPlus as the underlying simulation engine. Using a template simulation file with strings in place of parameter values, jEplus enables the automatic processing of large arrays of simulation trials.

An initial template file was created by inserting unique strings in place of parameter values in HVACGenerator. The next step was to set up our simulation trial within the jEplus GUI (Yi Zhang and Korolija 2010).

The above random trials were simulated in batch-mode using jEPlus. Simulation results were collected in a MySQL database for post-processing.

### STAGE 4: COMPUTE GOODNESS-OF-FIT

The companion paper (Coakley et al. 2011) defines the formulae for computing goodness-of-fit (GOF). The GOF for each model is based on a weighted combination of Coefficient of Variation of the Root Mean Square Error (CV RMSE) and Normalised Mean Bias Error (NMBE). The criteria under scrutiny in our models are:

- Electrical consumption (kWh)
- Heat energy consumption (kWh)
- Zone temperatures (°C)

The ASHRAE- Guideline 14 document (ASHRAE 14 2002) stipulates that the calibrated computer simulation model should be accurate to within 10% for the NMBE and 30% for CV(RMSE) relative to hourly measured data.

In order to perform a direct comparison, it was necessary to perform some pre-processing of our simulation and measured data.

### Electrical data Pre-Processing

Measured electrical data from the Building Management System is recorded in the following formats:

- Cumulative daily total (kWh)
- Cumulative weekly total (kWh)
- Cumulative monthly total (kWh)
- Present electrical usage (kW)

Data from the ‘present electrical use’ sensor was taken and averaged to compute an hourly average power consumption (kWh). Simulated electrical data in EnergyPlus is output in Watt-hours. Therefore, this was converted to hourly average power consumption (kWh).

### Heat Energy Consumption

Measured heat energy consumption from the low-pressure hot-water (LPHW) meter is similarly recorded using cumulative daily, weekly and monthly totals as well as current rates. However, energy consumption is only recorded on the heat meter in increments of 40kWh. This means that it is impossible to compare hourly averages from EnergyPlus with measured heat energy consumption. For the purpose of this initial trial, we compared daily totals instead of hourly totals.

### Zone Temperatures

Since we are using a single-zone BES model, it was necessary to compute a similar average zone temperature from the measured room temperatures in the building. It was decided that the best approach here was to use a floor area weighted average.. Areas such as storage rooms, hallways and stairwells are excluded from this list as they are not currently monitored.

Table 3: Room Weightings

| TEMP. SENSOR            | AREA          | WEIGHT        |
|-------------------------|---------------|---------------|
| Basement Computer Room  | 56.44         | 0.1284        |
| Basement Open Plan      | 78.63         | 0.1788        |
| Basement Comms Room     | 5.47          | 0.0124        |
| GFlr North Library      | 77.45         | 0.1761        |
| GFlr South Library      | 46.49         | 0.1057        |
| GFlr Copy Room          | 7.35          | 0.0167        |
| GFlr Office             | 18.13         | 0.0412        |
| FFlr PC Room            | 15.86         | 0.0361        |
| FFlr Study Rm 6         | 10.80         | 0.0246        |
| FFlr Study Rm 8         | 16.00         | 0.0364        |
| FFlr Open Plan          | 107.07        | 0.2435        |
| <b>Total Floor Area</b> | <b>439.69</b> | <b>1.0000</b> |

## RESULTS

For the purpose of this paper, we are limiting our results to a selection of 100 random simulation trials, numbered 1-100 (Sim Ref). Each trial was compared to available measured data for the period May to December 2011. Also, the results presented here are also confined to hourly temperature and electrical data for the building as LPHW readings are not currently available at an hourly resolution.

However, a full scale sensitivity analysis including daily LPHW consumption comparisons will be incorporated into the final study.

The following tables rank the top 10 simulation trials based on their respective goodness-of-fit (GOF) to hourly measured data. Table 4 provides a comparison of average hourly zone temperatures (°C) while Table 5 provides a comparison for average hourly electrical consumption (kWh)

- NMBE = Normalised Mean Bias Error (%)
- CVRMSE = Cumulative Variation of Root mean Square Error (%)
- GOF = Goodness-of-Fit

Practically, we would like our calibrated model to capture the mean more accurately than month-by-month variation. For this reason, we are using a 1:3 weight for  $w_{CV}:w_{NMBE}$  in calculating our GOF, as adopted in Ashrae Guideline 14 (ASHRAE 14 2002).

Table 4: Average Zone Temperature Error (Hourly)

| SIM REF | NMBE(T) | CVRMSE(T) | GOF(T) |
|---------|---------|-----------|--------|
| 71      | 0.275   | 14.212    | 4.499  |
| 23      | 0.126   | 14.229    | 4.500  |
| 57      | 0.322   | 14.209    | 4.500  |
| 93      | 0.330   | 14.209    | 4.500  |
| 11      | 0.402   | 14.206    | 4.502  |
| 22      | 0.396   | 14.205    | 4.502  |
| 77      | 0.421   | 14.203    | 4.503  |
| 17      | 0.025   | 14.243    | 4.504  |
| 21      | 0.059   | 14.265    | 4.511  |
| 65      | 0.118   | 14.274    | 4.515  |

The above figures show reasonable agreement between measured and simulated zone temperatures. However, higher CVRMSE values point to model discrepancies at an hourly level. It should be noted that the current model does not account for detailed schedule variation. Since the primary function of this building is study/research, there tends to be greater fluctuation in occupancy schedules. At present, the model operates on a fixed weekday and weekend occupancy schedule which does not account for irregular activity levels around, for example around exam periods.

Table 5: Whole Building Electrical Error (Hourly)

| SIM REF | NMBE(E) | CVRMSE(E) | GOF(E) |
|---------|---------|-----------|--------|
| 77      | 4.928   | 69.048    | 22.146 |
| 93      | 2.256   | 69.948    | 22.184 |
| 57      | 1.982   | 69.998    | 22.185 |
| 22      | 3.657   | 69.948    | 22.289 |
| 11      | 3.831   | 69.947    | 22.305 |
| 71      | 0.038   | 71.260    | 22.534 |
| 68      | 12.429  | 68.554    | 23.598 |
| 23      | 4.694   | 74.252    | 23.743 |
| 9       | 13.330  | 68.189    | 23.768 |
| 17      | 7.721   | 76.390    | 24.841 |

The electrical data also shows reasonable mean correlation for the current stage of the model. Again, as expected, we recorded more significant discrepancies in the hourly deviation of the simulation model from measured values. Further refinement is required to match the load profile of the actual building. Specifically, this requires

The following two tables provide the same comparison of measured and simulated data using monthly averages, typical of many calibration case

studies to date. The figures clearly indicate a better correlation than the hourly comparison tables. However, these comparisons mask model discrepancies which may only become apparent at daily or hourly resolutions.

Table 6: Average Zone Temperature Error (Monthly)

| SIM REF | NMBE(T) | CVRMSE(T) | GOF(T) |
|---------|---------|-----------|--------|
| 18      | 0.054   | 3.831     | 1.212  |
| 72      | 0.046   | 3.833     | 1.212  |
| 84      | 0.004   | 3.833     | 1.212  |
| 87      | 0.027   | 3.834     | 1.212  |
| 37      | 0.031   | 3.835     | 1.213  |
| 3       | 0.077   | 3.830     | 1.213  |
| 28      | 0.045   | 3.835     | 1.213  |
| 12      | 0.056   | 3.838     | 1.214  |
| 49      | 0.042   | 3.836     | 1.214  |
| 32      | 0.069   | 3.838     | 1.215  |

Table 7: Whole Building Electrical Error (Monthly)

| SIM REF | NMBE(E) | CVRMSE(E) | GOF(E) |
|---------|---------|-----------|--------|
| 96      | 0.943   | 28.731    | 9.113  |
| 64      | 1.218   | 28.817    | 9.158  |
| 31      | 1.928   | 28.903    | 9.254  |
| 66      | 2.473   | 28.868    | 9.315  |
| 27      | 2.829   | 28.860    | 9.370  |
| 54      | 2.937   | 28.911    | 9.404  |
| 24      | 3.606   | 28.817    | 9.506  |
| 15      | 3.578   | 28.913    | 9.529  |
| 67      | 4.353   | 28.910    | 9.708  |
| 74      | 4.468   | 28.991    | 9.761  |

## DISCUSSION

This research has illustrated a number of key findings in relation to the realities of calibration of BES models to detailed measured data.

### Measured and Simulated Data

The reliability and accuracy of ‘calibrated’ BES models depends on the quality of the measured data used to create the model, as well as the accuracy and limitations of the tools used to simulate the building and its’ systems.

Throughout the course of this study, it has been found that it is very difficult to obtain the level of

data required for detailed calibration, even in modern buildings with relatively large quantities of data readily available. In addition, Building Management Systems are often not configured to collect and archive monitored data points. Since data storage and archiving incurs additional cost, it is typically up to the client to explicitly request this service from the BMS installers.

Limitations of simulation tools also influence the results and thus impact simulated performance data significantly. These limitations are either embedded in the simulation tool or caused by the particular use of a tool and included in input data (Maile 2010).

### Uncertainty in BES Models

As highlighted by Kaplan et al. (1990), it will never be possible to identify the exact solution to the calibration problem. Due to its’ highly underdetermined nature, it will always yield a non-unique solution (Carroll and Hitchcock 1993). This case study serves to highlight the level of uncertainty associated with individual model input parameters and, consequently, the final calibrated model.

This uncertainty creates a vast multi-dimensional solution space. The calibration approach outlined in this paper recognises this problem and uses random sampling techniques in an attempt to identify a selection of optimum solutions rather than just one.

Therefore, rather than using only one plausible calibrated solution to make predictions about the effect of intended energy conservation measures (ECMs), we use a small number of the most plausible solutions. Not only is one likely to obtain a more robust prediction of the energy and demand reductions, but this will also allow us to determine their associated prediction uncertainty (Reddy, Maor, and Panjapornpon).

### Hourly vs Monthly Calibration

Currently, most studies analyse model error using monthly data (Reddy 2006). However, this approach may hide inaccuracies which only appear at hourly or daily resolutions (Raftery, Keane, and Costa 2011) The presented case study provides a perfect example of this.

## FUTURE WORK

The next phase of research will involve conducting a full parametric analysis combining discrete, continuous and multi-dimensional variables. Solutions will be ranked using the presented GOF functions. A full-scale sensitivity analysis will then be used to determine influential parameters and isolate controllable parameters for building performance optimisation.

We also intend to implement pseudo-random Sobol sampling techniques as part of our analyses. This step may be achieved using R sobol package. (Burhenne et al. 2011)

So far, this study has focused on a limited selection of simple continuous parameters. However, we plan to implement analyses of discrete and multi-dimensional parameters during the next phase of research.

We also plan to implement novel visualisation techniques (Raftery and Keane 2011) in the analysis of highly ranked models as part of this methodology. This will aid in the identification of major model discrepancies and help to further guide the direction of parameteric analysis.

## CONCLUSIONS

This paper outlines the application of a new methodology for the calibration of detailed simulation models to measured data using a systematic, evidence-based approach.

Detailed building and HVAC system information was used to create an accurate initial representation of the building. Sources of information were assigned to a hierarchy depending on their judged level of reliability. This information was then used to quantify parameter uncertainty and assign probability density functions (PDFs). Random sampling was used to generate and process a large set of simulation trials.

The model was compared to hourly measured data. This ensures that the model represents actual building operation more accurately compared with an equivalent model calibrated to monthly data. The presented case study is also unique in that this is a naturally ventilated building, which presents challenges in relation to levels of air infiltration.

We discussed the challenge of calibrating BES models due to measurement and simulation limitations. We also outlined the case for identifying model uncertainty and the purpose of generating multiple possible solutions.

This research aims to form the basis for a scalable approach for the calibration of generic BES models.

## ACKNOWLEDGEMENTS

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