Optimised IES-VE model calibration methodology integrating IoT, smart meter and BMS data

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Abstract

In this paper, we present a model-agnostic calibration methodology derived from IES' best practices and calibration guidelines. The calibration methodology relies on a 3-stage process that consist of (1) checking input priority matrix and SA results, (2) creating data-driven profiles for high priority inputs, and (3) determining and deriving high-priority parameters. The process uses data analysis techniques, Sensitivity Analisys (SA) and optimisation tools to maximise model accuracy and minimise calibration efforts.

IES headquarters, an office building in the UK, is presented as case study. A model of this building used for ongoing commissioning has been calibrated at hourly level. Internal gains (i.e. lighting, equipment and occupancy) are derived from IoT sensors and included in the simulation as Free-From-Profiles (FFPs). Room heating setpoints are included in the simulation as Parametric Profiles (PPs). Sensitivity analysis and Optimisation-based parameter search is done by grouping spaces with similar-end use to minimise the number of parameters. Electricity and air temperature calibrated to match utility data achieving a NMBE, CVRMSE and RMSE within recommended thresholds. Prediction error for air temperature outputs are minimised simultaneously to ensure that the model represents the building at space level. We show that use of metered data and automated tools can improve the quality of the model outputs at energy and space level with lower consultancy efforts.

Introduction

Buildings account for 40% of the global CO_2 emissions (Ahmad et al., 2016). In the UK, buildings account for 37% of the total annual greenhouse gas emissions (Committee on Climate Change, 2013). For the case of office buildings, it is expected that 20% of savings could be achieved by implementing minor energy conservation measures (IPCC, 2014). Additional major cost-effective actions could reduce energy demand up to 40% (Lewry, 2016).

Building Energy Simulations (BES) have been traditionally used during the design stage to inform design decisions (Manz et al., 2018), ensure occupants' comfort (ASHRAE Standard 55-2013, 2013), ensure compliance with energy efficiency codes (Pacific Northwest National Laboratory, 2016), gain credits in building rating systems, such as LEED and BREAM (Kestner et al., 2010), and determine building performance related to a regulation or standard, e.g. Energy Performance Certificates (EPCs).

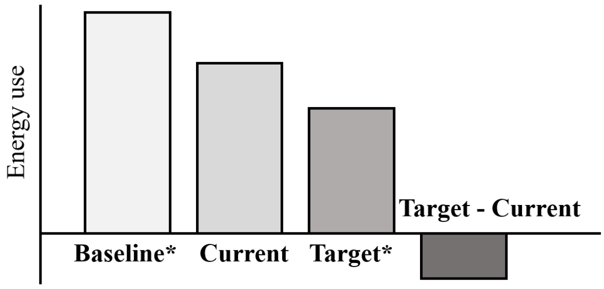

*Figure 1: Example of three types of energy use metrics: baseline, current and target. Baseline and target metrics (marked with *) are calculated using calibrated models. Source: Adapted from ISO (2016).*

During the operational stage, a calibrated model can be used for establishing a baseline and target energy use (see Figure 1), energy savings estimation (M&V) (EVO, 2002), fault detection and diagnostics (FDD) (Zimmermann et al., 2011), enhance building intelligence through model predictive control (MPC) (Aftab et al., 2017), enabling model-free control techniques such as Reinforcement Learning (RL) (Brandi et al., 2020), evaluation of demand-response (DR) technologies (Seitenfus et al., 2019) and prediction of future savings as a result of retro-commissioning activities or large renovations (Bande et al., 2019).

In Measurement and Verification (M&V), which can be defined as the process of determining the amount of savings obtained through an Energy Conservation Measures (ECMs), calibrated simulation models are used to (1) establish a baseline energy consumption in order to compare to energy consumption before and after implementing an ECM and eventually estimate savings, (2) adjust the baseline energy consumption in case a change occurs, such as occupancy hours or addition of new equipment, (3) assess the impact of a single ECM when multiple ones have been implemented at the same time and no individual measurement is in place and (4) reduce monitoring waiting time after ECM for early savings estimation.

The use of BES during the operational stage is subject to a successful model calibration effort which can be defined as "the process of reducing the uncertainty of a model by comparing the predicted output of the model under a specific set of conditions to the actual measured data for the same set of conditions", (ASHRAE, 2002). Without calibration, is not possible to determine the degree of uncertainty of the model with respect to the studied building.

However, model calibration is widely recognised as a time consuming activity, exclusive for scientific research and it often requires experienced engineers with knowledge about the building and its characteristics, The most common challenges are (Fabrizio and Monetti, 2015):

- Lack of standardisation: The workflow carried out is reliant on the users' own knowledge and experience, which can differ vastly between consultants. Additionally, there is a general consensus about the lack of defined methodology that ensures completeness, consistency and transparency (Raftery et al., 2011)
- Costs: Due to the lack of standardisation and the complexity involved in creating a calibrated model, the modelling process is significantly more time intensive than standard compliance models.
- Model input data: Calibrated models require large amounts of input data to complete the process, where models of greater complexity require greater amounts of data. As the process is user determined, it can be difficult to identify the most important datasets to focus on to achieve the calibration metrics at least effort. This further increases the time and cost requirements of the calibration process (Wang et al., 2019).
- Uncertainty: During manual calibration, a deterministic approach is typically adopted. However, not all data will impact the results of the model to the same degree. For this reason, it is important to identify, throughout a screening analysis, the parameters that influence the most the building model, such as occupancy, weather, sensors' accuracy an others; and define their level of uncertainty.
- Lack of automation: The calibration process is a manual one which relies on the experience and skills of the modeller.

Recently, the guideline CIBSE TM63 (CIBSE, 2020) introduces a whole building calibration and has been widely tested and proven for building energy model calibration. The process relies on Sensitivity Analysis (SA), Optimisation-based parameter derivation and iterative model evaluation. The guideline also recommends cross-checking space level simulation outputs such as air temperature and CO_2 concentration to ensure that there is a match between the measured and simulated data at space level.

Additionally, the recent cost reduction in sensors from buildings coming from Smart Meters (AMR), Building Management Systems (BMS) and Internet of Things (IoT) can improve the quality of the calibrated model. Also, richer input data can reduce the effort required during the calibration process by reducing the number of assumptions made to the model, e.g. actual start/stop times of heating/cooling plants, temperature setpoints and occupancy profiles.

In this work, we present an iterative calibration methodology and tools that not only supports but also complements the CIBSE TM63 guideline. This methodology is aimed for buildings with available sensor data consisting of three high-level stages: (1) check input priority matrix and SA results, (2) create data-driven profiles for high priority inputs, and (3) determine and fine-tune high-priority parameters. The process is repeated until the calibration metrics are achieved, i.e. uncertainty of the building is minimised to acceptable levels. An office building located in Scotland is used as case study and calibration results are presented according to recommended guidelines.

Methodology

The calibration methodology presented in this work exploits the relevant available data in the studied building, machine learning regression models, SA and optimisation tools with the objective of reducing calibration efforts and increasing model accuracy both at room level (e.g. air temperature) and energy level (e.g. electricity and cooling/heating demand).
The first sub-section introduces the input priority matrix concept, which is intended to work as a look up table indicating the data required and its relative importance for the model, based on its end-use. The process can be complemented with a SA outputs analysis if a model is available at this stage. In step 2, we present two methods for creating data-driven input parameters, the Free-Form-Profiles (FFPs) and the Parametric Profiles (PPs) which are used as inputs for the model. Step 3 consists of determining the high priority parameters by doing a Sensitivity Analysis (SA) followed by a robust optimisation-based tuning approach that minimises calibration metrics to recommended values in existing guidelines. These steps are model-agnostic but depend on the existence of measured data from the building especially from IoT sensors, BMS and AMR. Figure 2 shows a diagram with the presented methodology. Notice that this work describes the steps within the calibration methodology box.

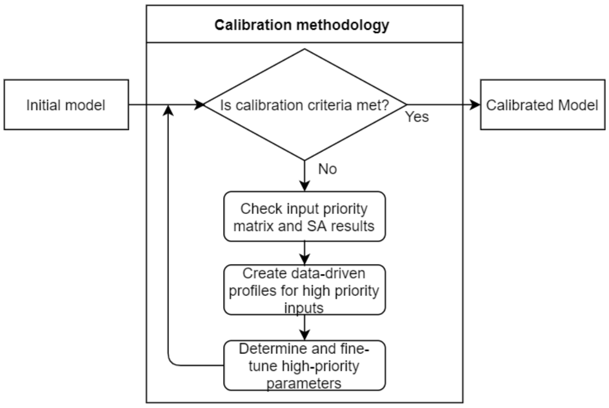

Figure 2: Model calibration workflow introduced in this work.

Step 1: Check input priority matrix and SA results

One of the most important steps when calibrating a model is to have a clear idea of its end use. Knowing the purpose of the calibrated model will allow the modeller to have a clear idea of the most critical parameters in a model, which potentially has thousands of them. Once the end-use of the model has been agreed, the use of input priority matrix provides the relative importance of model parameters and measured data. This matrix has been created based on a collection of IES's best practices for model calibration. The full explanation of the matrix is out of the scope of this paper, but the model applications considered in this matrix are:

- Long-term assessment
- Urban energy simulations
- Model-based commissioning
- Pre-occupancy commissioning
- Post-construction commissioning
- Retro-commissioning
- Measurement and verification

Parameters are divided into static (e.g. U-Values) and dynamic (e.g. setpoints, internal gains, weather data), as well as required measured data for calibration (e.g. monthly, hourly, sub-hourly). An example of the relative importance of parameters and energy data for a model that is intended to be used for retro-commissioning is presented in Figure 3.

A follow-up work will describe in more detail each of the model applications, including the justification of the importance assessment. However, the intent is that a model should be as reliable and accurate as needed, not as possible, while satisfying the requirements of calibration standards.

The CIBSE TM63 guideline suggests the use of a SA study to determine the relevant inputs. This step is also considered in the present methodology and proposed the use of a SA solution based on the Morris method (Campolongo et al., 2007). This method calculates the elementary effects (EE) to identity important inputs in large models. This method has

	Model Inputs	Retro-commissioning
Fixed Parameters	*Site Plan Drawings*	High
	Building Geometry (elevations, sections & floor plans)	High
	U-Values of Materials	Medium
	Infiltration	Medium
	Thermal Inertia	Medium
	Reflectiveness of materials	Medium
	HVAC Layout & Schematics	High
	HVAC Equipment Schedules & Specifications	High
	Lighting Layout	Medium
	Plug loads	
Dynamic Parameters	*Room setpoints*	High
	Free cooling ventilation strategies	High
	Internal gains	Medium
	HVAC information	High
	Control Strategies	Medium
	Lighting Schedules	High
	Equipment Schedules	High
	System Schedules	High
	Occupancy Schedules	High
	Site Weather Data	High
	Measured Data	
Measured	*Monthly Electricity Bills*	Low
	Monthly Heating Bills	Low
	< Hourly Electricity Data	High
	< Hourly Heating Data	High

Figure 3: Example of relative importance of parameters and measured energy data for calibrating a model intended for retro-commissioning.

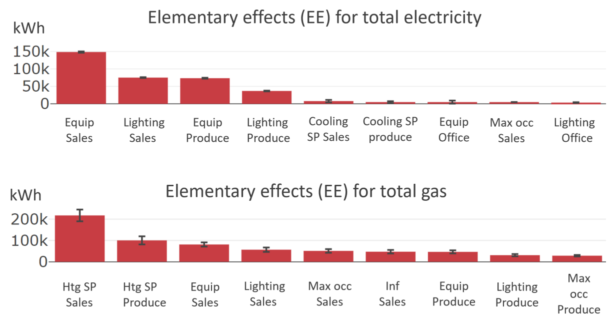

Figure 4: Example of SA results for an early-stage warehouse model for Electricity and Gas consumption. Parameters with higher relative impact in the selected model output are sorted in descendent order.

been successfully used for model calibration and is preferred due to its relative low-computational costs and results explainability (Kristensen and Petersen, 2016). An example of a SA study of an early stage model of a warehouse is presented in Figure 4. According to these results, equipment gains in the sales space is the parameter that impact the most the total electricity demand and the heating setpoint on the same space has the largest impact on gas demand.

However, at this stage we consider the that SA results have complementary role to the matrix. While a SA study is a more objective method to determine parameter importance compared to best-practice criteria, it is difficult to carry out a study to determine relative importance between dynamic (time-series) and static inputs. Also, a SA study done without any en-

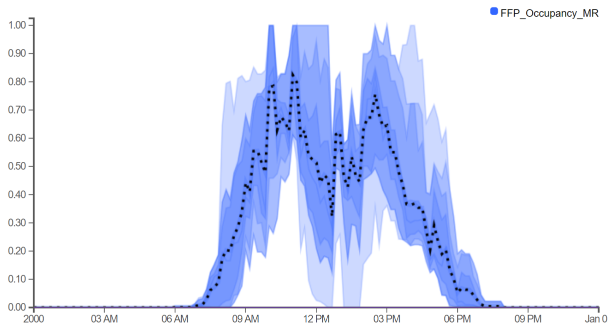

Figure 5: Example of observed trends from motion sensors in a building.

gineering criteria will likely have an excessive number of parameters, specially when time-series inputs are considered. Hence, the list of inputs is the result of both the priority matrix and SA results.

Step 2: Data-driven time-series input data

In this step, the aim is to take advantage of existing time-series data and incorporate it into the model in the form of Free-From-Profiles (FFPs) or Parametric Profiles (PPs). In this sub section, we describe them in detail and provide example of the kind of situation where each alternative is more adequate.

FFPs are used to import data coming directly from a third-party source, e.g. a machine learning (ML) model. An application of an ML model in the context of model calibration is the Trended daily profiles, a data driven adaptation of a technique defined as “day-typing” by Reddy (2006). ML regression models are used to generate a typical day for main occupied spaces for each day of the week. Hour, Day of the week, holidays and daylight saving time behaviours can be captured in the model, making it possible to account for typical occupancy behaviours not only during the calibration stage but also during model deployment. An example of observed motion trends is presented in Figure 5. Trended profiles can then be extrapolated for the rest of the year and also to fill in gaps in the datasets. These profiles are then imported to the model created in IES-VE as FFPs. Additional trended inputs may include lighting usage and small equipment usage patterns that can be obtained from short-term measurements and extrapolated over the calibration period.

PPs are useful to characterise dynamic inputs that can be largely explained by a set operation rules. PPs can be generated using syntax expressions based on current hour of the day, outdoor temperatures, occupancy levels and can be assigned to specific days. E.g. Weekends and weekday setpoint PPs may be enough in some cases to describe the whole-year heating profiles. Additional inputs that can be described with PPs may include window-usage trends, HVAC on/off schedules, or ventilation rates. It is possible also to combine Trended profiles with parametric profiles, to describe a building with or without COVID-19 social distancing measures.

Step 3: Determine and fine-tune high-priority parameters

A BES model has thousands of inputs and it is not possible to determine all of them by direct measurements due to resource constraints, hence most of the time is imperative to derive inputs with high importance for the simulation in lieu of direct measurements. This step is subdivided in (1) determine the impact due to the uncertainty of high priority parameters by doing a SA study and (2) fine-tune shortlisted parameters. Calibration metrics are the main driver to determine if the uncertainty of an input is relevant and whether the parameter fine-tuning is the optimal.

Calibration metrics for energy outputs are the Normalised Mean Bias Error (NMBE), defined in Equation 1, and the Coefficient of Variation of the Root Mean Squared Error (CVRMSE), defined in Equation 2.

$$NMBE(\%) = \frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)}{(N-P)\times\mu} \times 100\% \tag{1}$$

$$CVRMSE(\%) = \frac{\sqrt{\frac{\sum_{t=1}^{N}(y_t-\hat{y}_t)^2}{N-P-1}}}{\mu} \times 100\% \tag{2}$$

Following the CIBSE TM63 guideline, the recommended calibration metrics for non-energy measurements, such as air temperature and CO_2 concentration include the Root Mean Squared Error (RMSE), defined in Equation 3, and the Mean Absolute Error (MAE), defined in Equation 4.

$$RMSE(unit) = \sqrt{\frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{N-1}} \tag{3}$$

$$MAE(unit) = \frac{\sum_{t=1}^{N}|y_t - \hat{y}_t|}{N-1} \tag{4}$$

These metrics have thresholds depending on whether the simulation is calibrated at monthly or hourly intervals, as presented in Table 1. However, for time-series sensor data the monthly aggregation does not apply.

Table 1: NMBE and CVRMSE calibration thresholds for monthly and hourly intervals according to ASHRAE (2002) and CIBSE (2020).

	Monthly	**Hourly**
NMBE	5%	10%
CVRMSE	15%	30%
RMSE$_{temp}$	N/A	1.5 °C
MAE$_{temp}$	N/A	1.5 °C

SA study for calibration metrics

To determine the impact that missing or uncertain parameters have on the calibration metrics, a SA

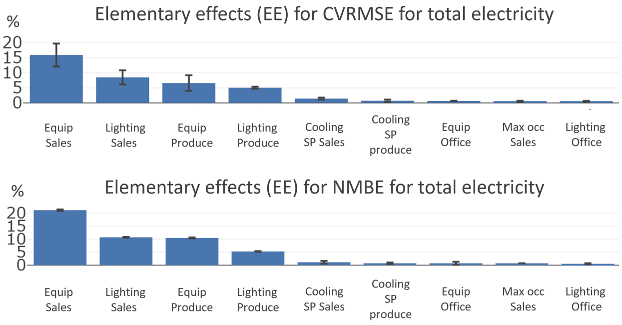

Figure 6: SA for calibration metrics outputs for electricity use.

study based on the Morris method similar to the previous step is required. The difference in this step with respect to the previous SA, is that the elementary effects are not in terms of model outputs but in calibration metrics. The outputs of the SA are useful to determine which variables can be shortlisted in the next sub step. An example of the SA outputs for calibration metrics in a simple Warehouse model are presented in Figure 6. According to these results, equipment gains in the sales space is the parameter that impact the most the calibration metrics (i.e. CVRMSE and NMBE) for electricity use.

Fine-tune shortlisted parameters

Shortlisted parameters can determined by using a hierarchy of information sources and by optimisation-based parameter search. Raftery et al. (2011) suggests a hierarchy of information sources. In order of priority, preferred sources are:

1. Data logged measurements
2. Short-term measurements
3. Observation from site survey
4. Interview to operator
5. Operation manuals
6. Commissioning documents
7. Benchmarks
8. Standards, specifications and guidelines
9. Design stage information

In order to fine-tune the final parameter values, an optimisation-based method using the Ant Colony Optimisation (ACO) algorithm is used (Dorigo et al., 2006). The cost function is designed to minimise all the calibration metrics errors simultaneously. The goal of the optimisation function consists of minimising the average of the Range-Normalised Root Mean Squared Error (RNRMSE) for all outputs that have metered data simultaneously. The intention of this approach, is to ensure that space level outputs are represented during the parameter search so that the algorithm receives a penalty if the parameters deviate from space level measurements. Chakraborty and Elzarka (2018) proposed RNRMSE as an alternative metric that normalises the RMSE by the range of the data, as defined in Equation 5. RNRMSE can provide a more meaningful representation of how the model fits all the measured data regardless its scale, which translates in a more robust optimisation algorithm.

$$RNRMSE(\%) = \frac{\sqrt{\frac{\sum_{t=1}^{N}(y_t-\hat{y}_t)^2}{N-1}}}{range(y)} \times 100\% \qquad (5)$$

The optimisation problem is then defined as:

$$\min_x f(x)$$
$$\text{where } x = \sum RNRMSE_{output}$$

Case study: the Helix building

The helix building is an office type building with a floor area of 2,900 m^2 and it was constructed post 2000s. The building has natural ventilation and heating is provided by a biomass (main) and natural gas (backup) boilers. The building accommodates around 180 people. The building is controlled by two thermostats. The typical temperature setpoint is 23 °C, with a night setback of 15 °C for both of them. The thermostat has two typical days: working and weekend day. Additionally, a server room is equipped with a cooling unit (mini-split) that keeps the equipment at the correct operational temperature. Currently, the building has 14 indoor environmental sensors at desk level, plus 5 roof-level additional sensors. These sensors communicate to a gateway every 10 minutes with a 5-minute data sample interval. Additional measurements include relative humidity, CO_2, motion and lighting levels (lux).

An existing IES-VE model was updated with the current building layout, constructions, orientation and external shading elements. A 3D view of the model is presented in Figure 7. The heating system has been modelled using Apache HVAC, an IES-VE module that allows detailed dynamic modeling of systems, equipment, and controls (IES-VE, 2012). Using this functionality, steel horizontal radiators with a 20 °C reference temperature difference have been included in all required rooms. Heat output is 1 kW per unit, similar to the manufacture's design value. Weight of the radiator was estimated to be 40 kg with a capacity of 9.9 liters, i.e. the simulation takes into account the mass of water that needs to be heated within the radiator before the room starts heating up and the heating inertia after the system switches off. Additionally, radiators have a local proportional controller to simulate the installed thermostatic radiator valves (TRV). The server room is conditioned with a simplified mini-split HVAC system.

Case study: Input priority matrix for ongoing commissioning

The calibration period is from the 01-October-2019 to 01-November-2019. The model will be calibrated for

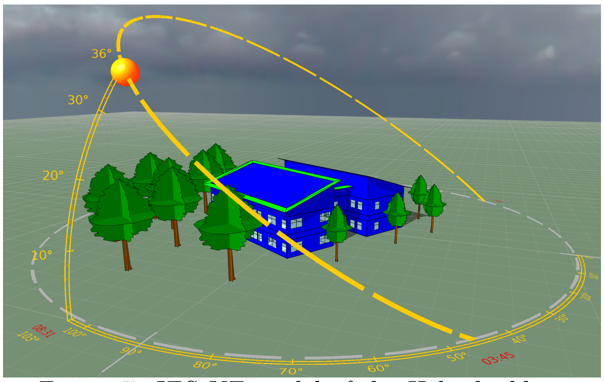

Figure 7: IES-VE model of the Helix building.

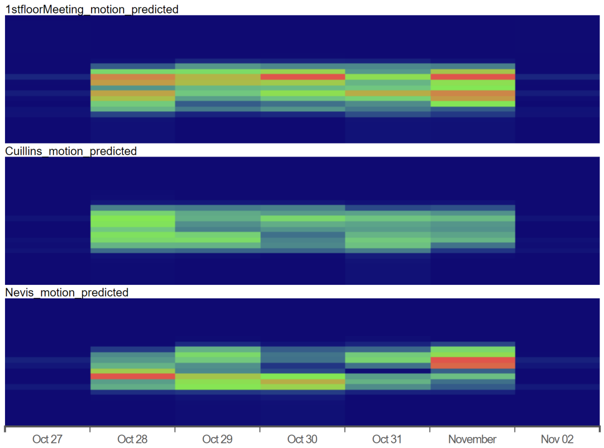

Figure 8: Motion trends for three meeting rooms in the Helix building, where blue means no motion and red means high motion periods. The motion is used as a predictor of occupancy and equipment gains modulation.

electricity use and space air temperatures at hourly intervals with a 2-minute simulation timestep. The application of the model is ongoing commissioning. This is a typical application of a calibrated model that can be used to constantly interrogate measured variables in a building and spot inefficient operations as they occur. According to the input priority matrix, fixed parameters with high importance include HVAC layout and schematics and HVAC equipment and specifications. Relevant dynamic parameters are: room setpoints, site weather data and schedules (e.g. lighting, equipment, system and occupancy).

Case study: Data-driven profiles for main occupied rooms

Motion detection in various areas of the buildings are used as a proxy value to determine occupancy,lighting and equipment profiles, see Figure 8. These trends are generated using a machine learning regression model for the occupied areas under the assumption that motion is a significant predictor of internal gains, and that it can be correlated with independent variables such as day-of-week, time-of-day, holiday calendar and weather variables. The occupancy trends are exported to the models via FFPs.

Heating setpoints are derived from air temperature readings for both weekday (Figure 9) and weekends

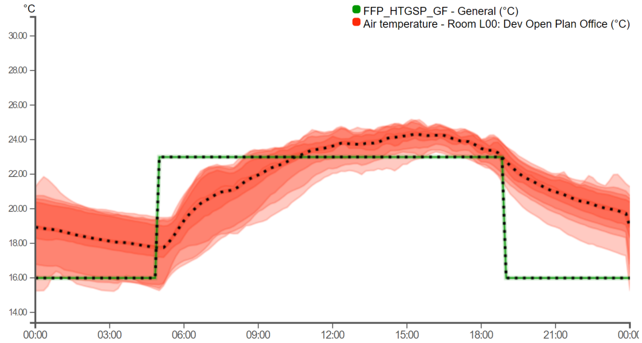

Figure 9: Setpoint estimation for weekdays. Red region shows an overlay view of air temperatures across weekdays, green line represents the setpoint which was exported as a PP to the IES-VE model.

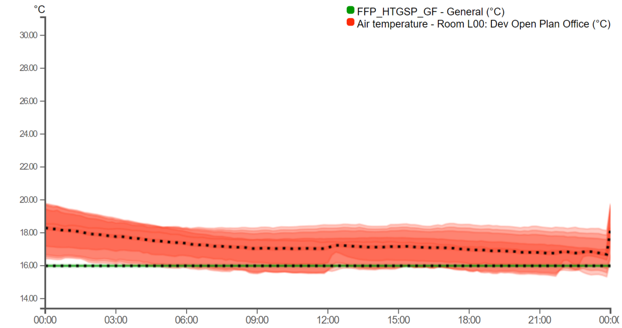

Figure 10: Setpoint estimation for weekends. Red region shows an overlay view of air temperatures across weekends, green line represents the setpoint which was exported as a PP to the IES-VE model.

(Figure 10). Using overlay plots, it is possible to visually determine if a temperature setpoint has occurred during a given month or week. A PP of the setpoint for each relevant room of the building was created and assigned to the model.

Case study: Determine and fine-tune high-priority parameters

For this model, weather data is obtained from a weather station located in the rooftop complemented with METeorological Aerodrome Reports (METAR) data from a station located at Paisley Airport in Glasgow. Fixed parameters, such as U-values and HVAC specifications, are calculated using as-built drawings and energy audit information. A summary of the initial high-priority inputs are explained in the following list. Notice that uncertain parameters are highlighted in bold.

- Trees added as local shading
- Ground temperature based on OAT 30-day moving average
- U-Values for Roof 0.155 W/m^2K Walls 0.26 W/m^2K
- **Initial estimated infiltration rate of 0.25 ACH**
- **Initial estimated lighting density 8 W/m^2**
- **Initial estimated equipment 12 W/m^2**
- **Initial server room cooling sp 23 °C**

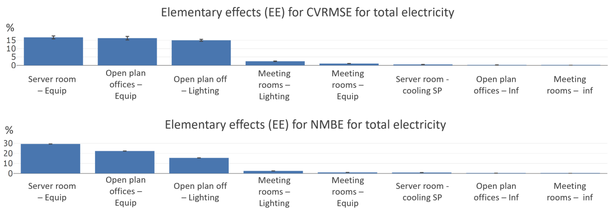

Figure 11: EE for electricity in terms of CVRMSE and NMBE.

Once FFPs for internal gains, PPs for setpoints, static inputs and weather data have been assigned to the model, the uncertain parameters are ranked in terms of relative impact to the calibration metrics. To avoid an excessive number of parameters, spaces were grouped by activity: Meeting rooms, open plan office, and server room. The SA algorithm requires a range of values for each of the input parameters. Using the SA IES tool, it is possible to change the value of a space or a group of spaces via a scaling factor or absolute values. In this case, all parameters that represent internal gains have a range based on a scaling factor between 0.7 to 1.3, which represents the range of the uncertainty. The cooling setpoint temperature of the server room, on the other hand, is represented as a range of absolute values. All the parameters and ranges are presented in Table 2.

*Table 2: Full list of parameters that may need to be fine-tuned. Shortlisted parameters for optimisation are marked with a star character *. We selected all parameters due to the large number of measurements available for calibration.*

Parameter	Abs/Scale	Range
Open plan offices - Equip*	Scale	0.7-1.3
Open plan offices - Lighting*	Scale	0.7-1.3
Open plan offices - Inf*	Scale	0.7-1.3
Meeting rooms - Equip*	Scale	0.7-1.3
Meeting rooms - Lighting*	Scale	0.7-1.3
Meeting rooms - Inf*	Scale	0.7-1.3
Server room - cooling SP*	Abs	21-24
Server room - Equip*	Scale	0.5-2

The SA for calibration metrics both for electricity, in terms of CVRMSE and NMBE, and air temperatures, in terms of RMSE and MAE, are calculated a number of levels 4 and 30 samples, which translates into 350 total simulations. The process was calculated using an 16-core and 32 GB RAM virtual machine. The total calculation time was 3352 seconds. Figure 11 shows the EE for electricity demand during the calibration period. Equipment gains in the server room are the main single relevant parameter that impacts the calibration metrics for electricity. On the other hand, infiltration values have negligible impact on electricity, since heating is provided by a biomass boiler, however, the value is not zero probably due to the impact on cooling loads.

Figure 12 shows the EE for air temperature in a selected meeting room during the calibration period.

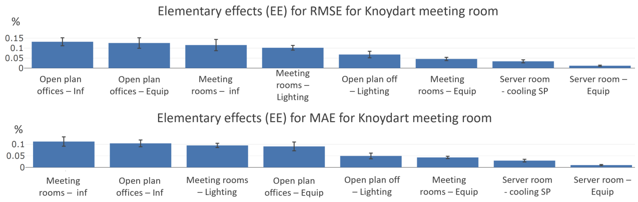

Figure 12: SA parameters for air temperature in an meeting room in terms of RMSE and MAE.

Table 3: Calibration metrics for hourly electricity use.

	CVRMSE before	CVRMSE after
Electricity	70.35% °C	**15.89%**
	NMBE before	**NMBE after**
Electricity	-40.48% °C	**-7.09%**

Results are not as straightforward in this case. The main parameter that drives the RMSE for air temperatures are the infiltration rates from the open areas.Whereas the infiltration rate of the meeting rooms is the main parameter that drives changes in MAE. On the other hand, there is an agreement that parameters related to the server room are not relevant for this meeting room.

Based on the SA results and the number of model outputs that can be used to calibrating the model (eleven), it was decided to leave the eight parameters for the actual calibration process. The total number of simulation was 500, this number is product of 50 iterations and a population number of 10. The process was calculated on an 16-core 32 GB RAM virtual machine and the total calculation time was 4394 seconds.Table 3 shows the calibration metrics before and after for electricity demand. Notice that the new metrics are below the calibration thresholds.

Table 4 shows the calibration metrics before and after for air temperature in selected spaces. Even though the calibration metrics for air temperature were already below the recommended threshold, most of them showed an additional improvement. These results suggest that no compromise was required to meet the calibration metrics for electricity.

Case study: Results comparison

After optimisation is completed, it is possible to recover the model parameters with their original units. Parameters before and after optimisation are pre-

Table 4: Calibration metrics for air temperatures in selected rooms.

Space (Group)	RMSE before	RMSE after
Nevis (Meeting room)	1.42 °C	**1.24 °C**
Cuillings (Meeting Room)	0.98 °C	**0.79 °C**
Grampian (Meeting Room)	**1.22 °C**	1.36 °C
Consultancy (Open area)	0.97 °C	**0.90 °C**
Support (Open Area)	1.07 °C	**1.06 °C**
Server room	0.72 °C	**0.47 °C**
Torridon (Meeting Room)	1.14 °C	**0.91 °C**
Training (Meeting Room)	1.32 °C	**1.29 °C**
Knoydart (Meeting Room)	1.26 °C	**1.24 °C**
Developers (Open Area)	1.22 °C	**1.08 °C**
Average	1.13 °C	**1.06 °C**

Table 5: Parameters before and after calibration. Average value of the spaces on each group.

Parameter	Updated
Open plan offices - Lighting	6.81 W/m^2
Open plan offices - Equip	9.56 W/m^2
Open plan offices - Inf	0.24 ACH
Meeting rooms - Equip	9.18 W/m^2
Meeting rooms - Lighting	10.01 W/m^2
Meeting rooms - Inf	0.55 ACH
Server room - Equip	39.78 W/m^2
Server room - cooling SP	23.63 °C

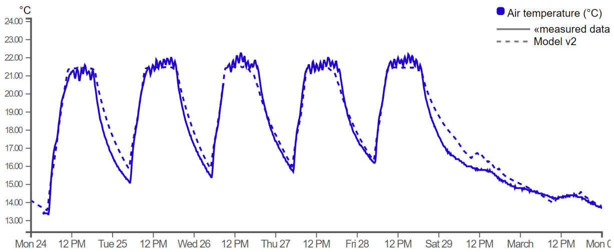

Figure 13: Simulated vs measured air temperature results during a week.

sented in Table 5.

The average RMSE has improved from 1.13 °C to 1.06 °C, both are well below the values recommended in CIBSE TM63. Air temperature results during a week within the calibration period are presented in Figure 13. In this plot, it can be noticed that there seems to be a close match between the simulated and metered temperatures, especially during the warm up and cool down times and the weekend.

On the energy side, electricity values are calculated when compared to sub-metered electricity readings covering the ground floor. These have been adjusted to remove the effect of a two-car electric vehicle (EV) charging unit connected to the building, due to the reason that EV charging station is outside the scope of the model, Figure 14.

It is worth noticing that the time taken to calibrate the model is now significantly reduced as a result of the automated SA and Optimisation. In total, around 860 simulations were required to achieve these metrics from which 850 were part of an automated process. The process was completed in less than 7 hours. Previous attempts to manually fine-tune uncertain parameters resulted in higher calibration metrics, e.g. CVRMSE > 25%; substantially higher consultancy time, e.g. three working days; with only visual estimations of the uncertainty at space level.

Conclusions

In this paper, we present a calibration methodology derived from IES' best practices and calibration guidelines. The calibration methodology is model-agnostic and relies on a 3-step process that consist of (1) checking input priority matrix and SA results, (2) create data-driven profiles for high priority inputs,

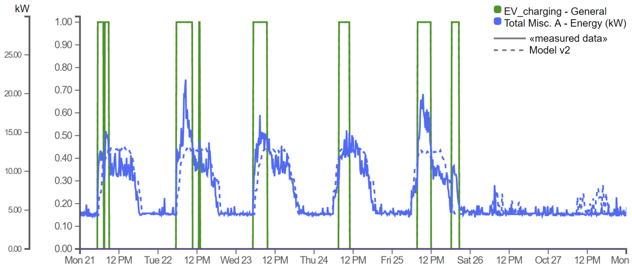

Figure 14: Measured (solid line) vs simulated (dashed line) electricity data for the ground used for electricity calibration of the model. Notice that periods when EV cars are being charged are not being simulated by the model.

and (3) determine and fine-tune high-priority parameters. The process relies on the use of specialised tools for Sensitivity Analysis, Optimisation-based parameter derivation and calibration metrics computation.

Using an office building in Scotland as a case study, we did an hourly level calibration of a model intended for ongoing commissioning. Internal gains modulation (i.e. lighting, equipment and occupancy) are included in the model as FFPs derived from time-series data from sensors using a machine learning regression model. Lighting and equipment intensity, infiltration and setpoints were determined for spaces grouped by activity, e.g. open office areas and meeting rooms. A SA determined the most relevant variables for the optimisation-based parameter search, and an ACO algorithm was used to fine-tune the final gains, infiltration rates and the server room setpoint.

Electricity calibration achieves a NMBE -7.09% and CVRMSE of 15.89%. Most of the calibration metrics for air temperatures were improved in average 6% and there were kept within the 1.5 °C recommended threshold. Based on these findings, we provide evidence that metered data can benefit the model prediction outputs both at the energy and space level and that SA and optimisation tools can speed up the calibration process.

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