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Calibration and Validation of Building Simulation Models for Overheating Risk Predictions: A Case Study of a Matched Pair of Test Houses in the UK

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Abstract: Increasing global temperatures and more frequent heatwaves pose a growing indoor overheating risk. To address this issue, building simulation models are commonly used to predict indoor overheating risks and implement effective mitigation strategies during the design phase. However, concerns have arisen due to evidence of discrepancies between simulated and real building performance, casting doubt on their reliability. This study seeks to enhance the accuracy of building simulation models in predicting overheating risks through a case study of matched-pair test houses, synthetically occupied and unoccupied, using Bayesian calibration. The findings underscore discrepancies between simulated and measured data, where simulated results did not exceed the TM59 criteria while observed data surpassed the threshold. Among calibration iterations, weather data, especially those associated with solar radiation, plays a pivotal role in improving the accuracy of indoor temperature predictions through the novel approach of incorporating uncertainties into weather variables.
Keywords: Overheating Risk Predictions, Building Simulation Model Accuracy, Bayesian Calibration, Uncertainties in Weather Data, Predictive Indoor Temperatures

1. Introduction

With recorded world temperatures on the rise, the risk of indoor overheating has also increased. In adaptation to warmer climates, the demand for space cooling increases (Salata et al., 2023). Passive cooling is one approach employed to meet the demand for cooling. While active cooling might seem straightforward solution, it increases energy usage and carbon emissions, which contradicts global warming mitigation efforts and the UK's goal of achieving net-zero carbon emissions by 2050. Building simulation models is invaluable for evaluating passive design strategies.

However, several studies have found disparities between simulated and observed results. For example, Calama-González et al. (2021) found that models overestimate temperatures. Symonds et al. (2017) suggested limited data on occupants, dwelling characteristics, and the local environment affect accuracy. Moreover, several studies have used building thermal models without validation. This is often due to the high costs associated with conducting measurements (Symonds et al., 2017). Overheating risk prediction necessitates accuracy because it requires precise temperature forecasts at specific time intervals where compensating overpredictions at one hour with underpredictions at another is not feasible, which makes it more challenging than energy consumption prediction (Roberts et al., 2019).

While Bayesian calibration has become a widely employed method for fine-tuning input parameters for building energy models and reducing disparities between simulated and observed data, it has primarily been applied to the aspect of energy consumption prediction. There remains a gap in its application to predict overheating risks or indoor temperatures.

Hence, this study aims to improve the accuracy of building simulation models in predicting the risk of overheating through Bayesian calibration in the case study house.

2. Methodology

The research approach employed in this study follows the depiction in Figure 1.

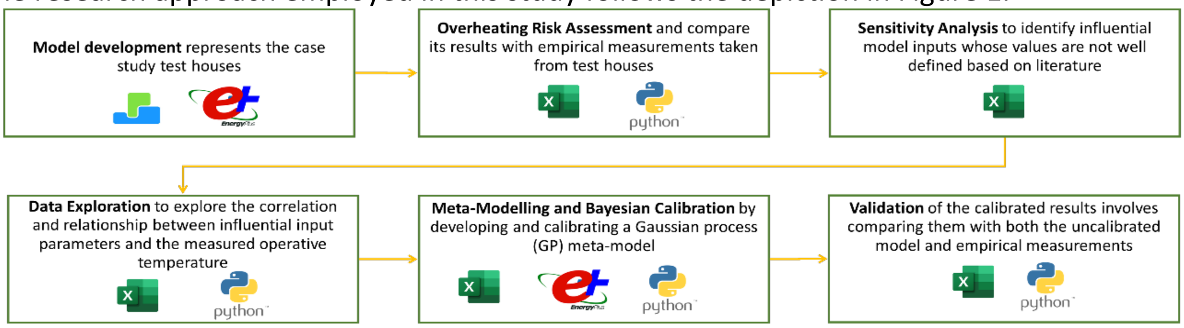

Figure 1. Methodology Flow Diagram

2.1 Model Development

The case study utilised secondary data from an open-access dataset by Roberts et al. (2022). It is a semi-detached 3-bedroom house built in the 1930s and retrofitted in 2016, located in Loughborough, United Kingdom (52°46'15.69"N, 1°13'25.30"W). One of the houses, the west house, is unoccupied, while another, the east house, is synthetically occupied. Both houses are naturally ventilated and have mirrored floor plans as shown in Figure 2.

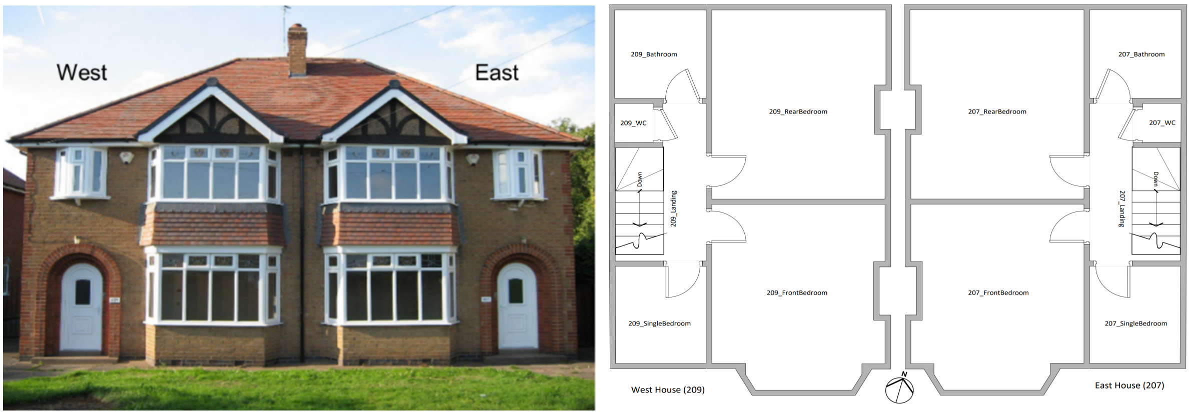

Figure 2. A Matched Pair House in this Study

The building model is developed in DesignBuilder and exported as a text-based input data file (idf) to EnergyPlus following the house information. The assessment was focused on the rear and front bedrooms on the first floor since the windows in both rooms face the same direction (south and north). Furthermore, the top floor appears to be overheated more than the bottom floor (Habitzreuter, Smith and Keeling, 2020).

A synthetic occupancy schedule was used in the occupied house to replicate the presence of real occupants, with the schedule set following Table 1.

Table 1. Schedule Settings in a Matched Pair of Test Houses

House	Description	Room	Windows open	Shading open	Internal doors open
West	Unoccupied	Bedrooms	Never	Always	Always
East	Occupied	Bedrooms	Always	8.00-22.00	8.00-22.00

Furthermore, for the occupied house model, internal heat gains were set following the measured values obtained from Plogg meters. These meters quantified the actual power generated by electric lightbulbs, which were configured in accordance with the TM59 guidelines for a three-bedroom apartment in a 24/7 occupancy scenario (CIBSE, 2017).

2.2 Weather Data

The weather data were sourced from four locations near the test house provided by Roberts et al. (2022). Weather variables are global horizontal irradiance, dry bulb temperature, relative humidity, cloud cover, wind speed, wind direction, and diffuse solar irradiance.

2.3 Overheating Risk Assessment

The operative temperature is used to assess overheating risk following TM59 (CIBSE, 2017). Both criteria, as follows, must be met for homes that are predominantly naturally ventilated:
Criteria A: From May 1st to September 30th, the total number of hours where the temperature difference (ΔT) is equal to or greater than one degree Kelvin (K) should not exceed 3% of the total occupied hours.
Criteria B: The operative temperature in bedrooms during 10 p.m. to 7 a.m. should not exceed 26°C for more than 1% of the total yearly hours.

2.4 Gaussian process meta-model and Bayesian Calibration

In pursuit of enhanced accuracy in predicting overheating risks in building simulation models, Bayesian calibration was applied to automatically adjust input parameters using observed data. This calibration method relies on the Bayesian framework developed by Huard and Mailhot (2006), which is represented by the following equation:

$$y(\widetilde{w}_i) = \eta(\widetilde{w}_i, \theta) + \delta(\widetilde{w}_i) + \varepsilon_i$$

Where: $\widetilde{w}_i = w_i + \alpha$

$\widetilde{w}_i$ = the vector of measured input variables associated with observation i, and corresponds to the true values w_i

α = additive error

This equation was customised to account for additive errors (α) in the measured weather variables. It was implemented using CmdStanPy in Python, with four parallel Markov Chain Monte Carlo (MCMC) chains. Each chain underwent a warm-up phase consisting of 500 iterations, followed by 500 iterations of sampling, resulting in a total of 2,000 iterations.

The calibration process occurs simultaneously with training focusing on the heatwave period in July 2021 (16th to 23rd). Additionally, the mathematical framework of the Gaussian process was incorporated for computer modelling within Bayesian calibration, directly adopted from Chong and Menberg (2018), to reduce computation time. After running the calibration, the Gelman-Rubin statistic ($\hat{R}$) was used to assess the MCMC chains convergence, ensuring that they fell within an acceptable range of 1.0 ± 0.1.

2.5 Validation

Validation of the calibrated model employed NMBE, RMSE, CV(RMSE) and GOF metrics to quantify the differences between uncalibrated and alternatively calibrated models, together with empirical measurements.

3. Results and Discussion

3.1 Overheating Risk Results

After developing the simulation model for the case study house, the evaluation of predicted overheating risks compared to empirical measurements revealed notable differences (Figure 3), which align with previous findings by Roberts et al. (2019) and Symonds et al. (2017). Regarding Criteria A, empirical measurement data indicates hours exceeding a 1-degree temperature difference threshold while simulations fail to recognise these occurrences.

Criteria B also accentuates these differences, as measured temperatures breach the 1% threshold during sleeping hours while all simulation models predict values below it.

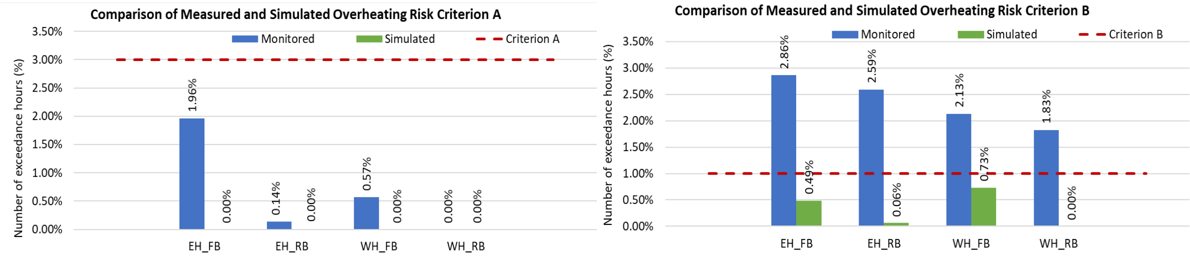

Figure 3. Overheating Risk Assessment Results of Simulated and Monitored data based on Criterion A and B

3.2 Sensitivity Analysis

A set of influential parameters was analysed based on the research conducted by Roberts et al. (2023). Their research encompassed manual calibration in the front bedrooms of the same test house. The RMSE results from their study were employed to calculate the relative change for each iteration, as illustrated in Figure 4.

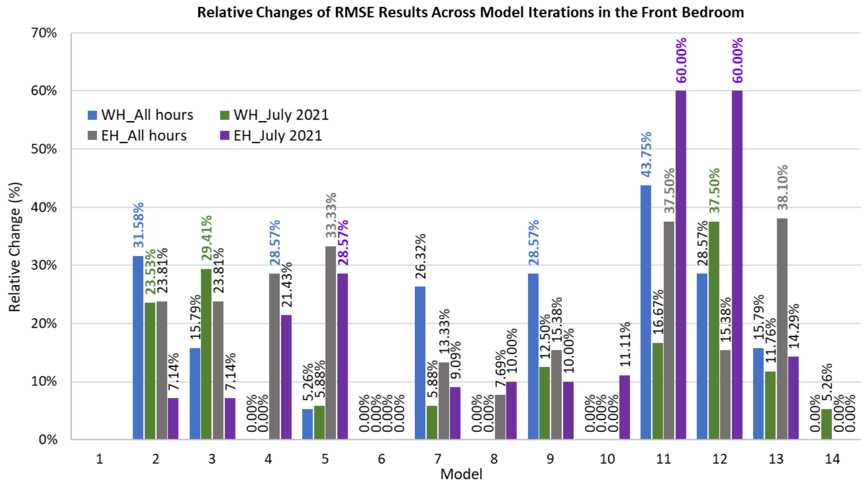

Figure 4. Relative Changes of RMSE Results Across Model Iterations in the Front Bedrooms

Roberts et al. (2023) have introduced changes to weather data variables, and their influence on the building model's performance has become evident (Models 2, 5, and 12). A modification in thermal mass was done in Model 11, and it also exhibited substantial relative changes. However, this adjustment resulted in higher thermal mass walls than those observed in real houses (Roberts et al., 2023), presenting a challenge in justifying its use for calibration.

3.3 Exploratory Analysis

To enhance understanding of the relationship between measured operative temperature and weather data variables, scatter plots and correlation matrices were conducted to identify patterns, trends, and correlations among these variables.

Dry bulb temperatures exhibit the strongest correlation with measured operative temperatures. Remarkably, global radiation demonstrates correlations with other weather variables, except wind direction, while humidity correlates with global radiation, diffuse radiation, cloud cover, and dry bulb temperature. These relationships were then used to group weather variables for the calibration process, resulting in 15 iterations.

3.4 Calibrated Models

During the calibration process in the period of heightened temperatures (20th to 23rd July), all iterations successfully converged within 2,000 iterations, as indicated by the $\hat{R}$ values.

Across the 15 iterations, mean predicted operative temperatures consistently had similar patterns for all bedrooms. Temperature fluctuations were observed, characterised by high values during the night and gradual decreases during the day.

In the front bedroom of the occupied house, model 14 (Global Radiation, Diffuse Radiation) exhibited the most significant improvements in accuracy. It shown a reduction of RMSE from 2.96°C to 1.76°C, CV(RMSE) from 10.40% to 6.16%, NMBE from 9.93% to 2.42%, and GOF from 10.17% to 4.69%. Models 13 (Diffuse Radiation) and 15 (Global Radiation, Diffuse Radiation, Cloud Cover) also showed substantial enhancements, with RMSE values of 1.76°C and 1.77°C, respectively, along with CV(RMSE) of 6.19% and 6.22%, NMBE of 2.40% and 2.42%, and GOF of 4.71% and 4.79%, respectively.

In the rear bedroom, model 15 (Global Radiation, Diffuse Radiation, Cloud Cover) yielded the lowest errors with RMSE reducing from 3.33°C to 1.86°C, CV(RMSE) reducing from 11.86% to 6.55%, NMBE from 11.43% to 2.45%, and GOF from 11.6% to 4.95%.

In the unoccupied houses, both the front and rear bedroom, models 13 (Diffuse Radiation) have the minimum values of validation metrics, with RMSE reduce from 2.37°C and 3.01°C to 2.13°C and 1.99°C, respectively, CV(RMSE) reducing from 8.39% and 10.88% to7.55% and 7.18%, respectively, NMBE from 8.25% and 10.78% to 5.22% and 5.20%, and GOF from 8.32% and 15.31% to 6.49% and 6.29%.

Overall, the calibrated models show lower accuracy errors in the operative temperature than the uncalibrated models (Figures 5-6).

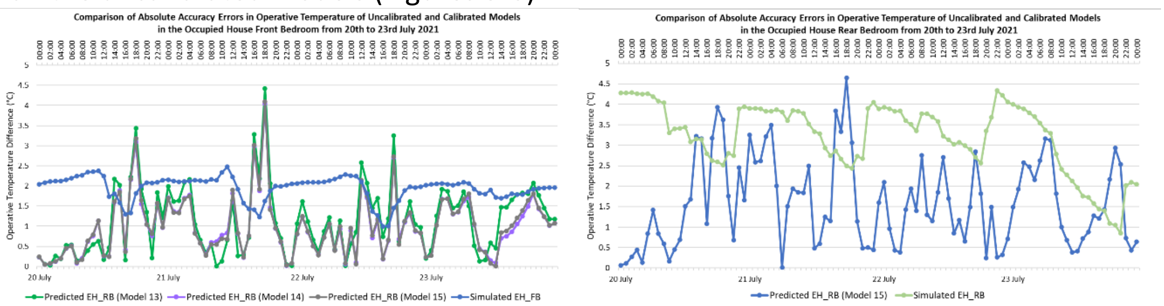

Figure 5. Comparative Analysis of Operative Temperature Accuracy Errors in Uncalibrated and Calibrated Models for the Front Bedroom (left) and Rear Bedroom (right) in an Occupied House

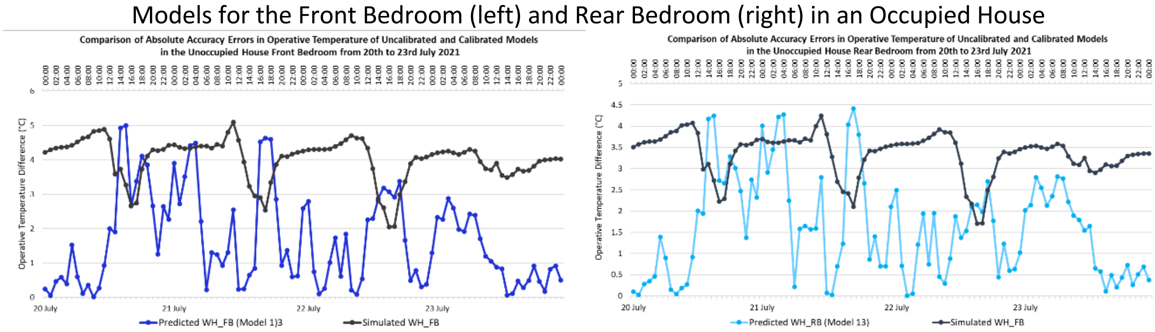

Figure 6. Comparative Analysis of Operative Temperature Accuracy Errors in Uncalibrated and Calibrated Models for the Front Bedroom (left) and Rear Bedroom (right) in an Unoccupied House

4. Conclusion

To conclude, this study reveals that the simulated results failed to show overheating risks, although the observed data showed risk occurrences. Notably, the measured data shows an overheating risk in the bedroom that exceeds criteria B. This emphasises the importance of improved predictive models.

This study identified weather data as a crucial parameter influencing the accuracy of model predictions. Incorporating uncertainties in weather data variables improved indoor temperature predictions during heatwave periods. Global radiation, diffuse radiation, and cloud cover contributed to a reduction in errors of up to 50%. However, the model still exhibited some limitations in capturing the intricate patterns of the predicted operative temperature.

5. Limitations and Future Study

This study encountered some limitations that should be acknowledged and recommended as areas for future study.

Firstly, the calibration process was focused on a specific heatwave episode in 2021. The extensive computational time required for the analysis made this focus necessary. While the calibrated models demonstrated improved accuracy during the heatwave, extending the training period could potentially enable the models to capture more nuanced patterns of indoor temperature over longer timeframes. Moreover, incorporating lag components in weather data during the calibration process might enhance the models' ability to capture intricate temperature patterns.

Secondly, the analysis incorporated several weather parameters. However, dew point temperature and direct normal radiation haven't been considered in the study, which may potentially influence the precision of the calibrated models.

Thirdly, this study focused on the EnergyPlus simulation software tool. Given the diversity of available tools, future research should explore the performance and accuracy of these alternative software choices.

Lastly, broadening the scope of future studies to encompass geographically diverse climatic conditions and focusing on real-world occupied buildings could have the potential to yield a more holistic understanding of models' predictive capabilities.

6. References:

Calama-González, C. M., Symonds, P., Petrou, G., Suárez, R. and León-Rodríguez, Á. L. (2021). 'Bayesian calibration of building energy models for uncertainty analysis through test cells monitoring'. Applied Energy, 282, p. 116118. doi: 10.1016/j.apenergy.2020.116118.

Chong, A. and Menberg, K. (2018). 'Guidelines for the Bayesian calibration of building energy models'. Energy and Buildings, 174, pp. 527–547. doi: 10.1016/j.enbuild.2018.06.028.

CIBSE. (2017). 'TM59 Design methodology for the assessment of overheating risk in homes 2017'.

Habitzreuter, L., Smith, S. T. and Keeling, T. (2020). 'Modelling the overheating risk in an uniform high-rise building design with a consideration of urban context and heatwaves'. Indoor and Built Environment, 29 (5), pp. 671–688. doi: 10.1177/1420326X19856400.

Huard, D. and Mailhot, A. (2006). 'A Bayesian perspective on input uncertainty in model calibration: Application to hydrological model "abc".' Water Resources Research, 42 (7). doi: 10.1029/2005WR004661.

Roberts, B. M., Abel, B., Allinson, D. and Crowley, J. (2023). 'Identifying the causes of discrepancy between measured and modelled indoor temperatures in two synthetically occupied test houses'. CIBSE Technical Symposium.

Roberts, B. M., Allinson, D. and Lomas, K. (2019). 'Prediction of overheating in synthetically occupied UK homes: dataset for validating dynamic thermal models of buildings'. Loughborough University. doi: 10.17028/RD.LBORO.8094575.V2.

Roberts, B. M., Allinson, D., Abel, B. and Lomas, K. (2022). 'Measured indoor temperature, weather, infiltration, and ventilation in synthetically occupied test houses: summer 2021, UK'. Loughborough University. doi: 10.17028/RD.LBORO.19308299.

Salata, F., Falasca, S., Ciancio, V., Curci, G. and de Wilde, P. (2023). 'Climate-change related evolution of future building cooling energy demand in a Mediterranean Country'. Energy and Buildings, 290, p. 113112. doi: 10.1016/j.enbuild.2023.113112.

Symonds, P., Taylor, J., Mavrogianni, A., Davies, M., Shrubsole, C., Hamilton, I. and Chalabi, Z. (2017). 'Overheating in English dwellings: comparing modelled and monitored large-scale datasets'. Building Research & Information, 45 (1–2), pp. 195–208. doi: 10.1080/09613218.2016.1224675.