Occupancy data at different spatial resolutions: building energy performance and model calibration

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Abstract

Occupancy is a significant area of interest within the field of building performance simulation (BPS). Through Bayesian calibration, the present study investigates the impact of the availability of different spatial resolution of occupancy data on the gap between predicted and measured energy use in buildings. The study also examines the effect of occupancy data on the quality of the constructed prediction intervals (PIs) using the Coverage Width-based Criterion (CWC) metric. CWC evaluates the PIs based on both their coverage and range. This investigation takes the form of an actual building case study, with nine months of hourly measured building electricity use, WiFi connection counts as a proxy for occupancy, and actual meteorological year (AMY) weather data.

In general, the accuracy of the building energy model improves with the occupancy and plug-loads schedule derived from WiFi data. Specifically, the Coefficient of Variation Root Mean Square Error (CV[RMSE]) reduced from 37% to 24% with an exponential improvement in the PIs quality compared to the results obtained with ASHRAE 90.1 reference schedules. However, the increase in prediction accuracy shrank to 5% CV(RMSE) and a comparable CWC upon calibrating the base loads of the reference schedules. Increasing the spatial resolution from building aggregated to floor aggregated occupancy data

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worsened the CV(RMSE) and CWC, suggesting trade-offs between parameter uncertainty and model bias/inadequacy. These results contribute to our understanding of the interactions between model complexity, simulation objectives, and data informativeness, facilitating future discussions on the right level of abstraction when modeling occupancy in BPS.

Keywords: Occupant modeling, Building performance simulation, Building simulation, Bayesian calibration, Uncertainty analysis

1. Introduction

Occupants have been identified as one of the six driving factors of energy use in buildings [1] and as a source of uncertainty with a significant impact on building performance simulation (BPS) [2]. Building occupants not only act as a source of internal heat gains, but their interaction with different building systems also exerts influence on a building's heating and cooling energy (HVAC system operations and efficiency), as well as its lighting and equipment loads [3, 4]. In an evaluation of 121 LEED certified buildings, Turner and Frankel [5] showed that significant variability exists between the design-phase model predictions and measured energy performance. Occupancy was hypothesized as a possible reason behind the discrepancies, citing differences in operational practices and schedules that were not anticipated during the energy modeling process. The perception that occupants causes a significant source of discrepancy between building energy simulation predictions and actual observations is further corroborated in an international survey of 274 BPS users across 37 countries [6].

1.1. Occupant behavior (OB) and building performance simulation (BPS)

In this paper, we define OB as a quantitative description of the influences that building occupants exert on building energy performance. Examples include the impact on energy use resulting from lighting and appliance usage, window opening, air-conditioning usage, etc [7, 8]. Behavior referring to observable stimulus-response or the way occupants act and interact with several factors that can be separated into various biological, psychological, and social contexts [9] is not addressed within the current paper.

BPS is often used to quantify the impact that OB might have on simulation predictions, energy-saving potentials of different energy conservation measures (ECMs), and performance of various building systems. For instance, Clevenger and Haymaker [10] quantified the uncertainties in BPS due to OB and found that the predicted energy consumption could differ by more than 150% when occupant-related inputs were all maximized or minimized. Sun and Hong [11] defined three different occupant behavior styles (austerity, normal, and wasteful) and showed that OB has a significant impact on ECMs such as zonal HVAC control and mix-mode ventilation because of their strong occupant interactions. Azar and Menassa [12] performed a comprehensive sensitivity analysis on OB related parameters. Their simulation results indicate that on average, heating setpoint temperature was the most sensitive parameter in small-size buildings located in climate zone 2 and that larger buildings were more sensitive to variations in lighting and equipment usage. Using a residential prototype building in EnergyPlus, O'Neil and Niu [13] showed that a 3.76% average coefficient of variation in OB related input parameters led to about 4% impact on HVAC annual and peak energy consumption.

To bridge these performance gaps, there has been increasing research concerning the modeling and simulation of occupant behavior in buildings [2, 14]. Occupant presence and behavior in BPS are commonly represented with diversity factors in the form of standardized hourly schedules or profiles. Default diversity factors are typically obtained from codes and standards such as the ASHRAE 90.1[1] [15] when actual schedules are unknown. A limitation of these standardized profiles is that they are not specific to the buildings being modeled and have been shown to differ substantially from actual diversity profiles [16, 17]. To overcome the limitations of its generality, multiple efforts have been undertaken to derive more reliable profiles. For instance, Davis and Nutter [18]

[1] http://sspc901.ashraepcs.org/documents/Addendum_an_Sched_and_Load.pdf

derived occupancy profiles for eight university buildings using data from various data sources (security cameras, doorway counting sensors, classroom scheduling data, and manual observations). D'Oca and Hong [19] applied a three-step data mining framework to occupancy data for 16 offices and identified four archetypal occupant patterns that can be transformed into typical working profiles of occupancy for use in BPS.

1.2. Modeling of occupancy

Considerable efforts have also been directed towards the development of more detailed occupant models to capture the complexity and wide variability (both spatially and temporally) in occupant behavior. These include probabilistic models that determines presence based on a probability function [20]; stochastic markov chain models that generates time-series of states based on the state attained at the previous time-step [21, 22]; and agent based models that involves the defining and modeling of autonomous individuals (agents), their mutual relationship, as well as their interaction with respective building spaces and systems [23]. However, complex models do not always provide better predictive performance. Using an out-of-sample test dataset Mahdavi and Tahmasebi [24] evaluated two existing probabilistic occupancy models and a non-probabilistic occupancy model. They found that the predictive accuracy of all three models was low in general and that the simpler non-probabilistic model performed better in view of short-term occupancy predictions. Using simulation, Gilani, O'Brien, and Gunay [25] concluded that deterministic models could reasonably represent the occupants' impact on the building's average annual energy use. However, the effect of individual occupants diminishes with building size. Additionally, increasing complexity is often associated with other issues that include onerous data requirements, an increasing likelihood of model overfitting [14, 26], as well as the introduction of uncertainties that may lead to identifiability issues during the parameter estimation process [27, 28].

1.3. Occupancy sensing for BPS

With advancements in occupant sensing and data acquisition technology, occupant information is becoming increasingly available and more easily accessible. According to Melfi et al. [29], occupancy can be defined by different occupant, spatial, and temporal resolution, and occupancy sensing can be categorized as either explicit or implicit. Implicit occupancy sensing involves the use of existing building infrastructure to measure occupancy because the interactions between occupants and the building systems can be used to determine occupancy information. On the contrary, explicit occupancy sensing involves the addition of specific occupancy sensing and detection capabilities and is often synonymous with high installation and maintenance costs [30]. The different occupancy monitoring and detection technologies include surveys, motion sensors (e.g., passive infrared (PIR) and ultrasonic detectors), vision-based sensors (e.g., video cameras), and radio frequency (RF) based sensors (e.g., ultra-wideband (UWB), radio-frequency identification (RFID), Wireless Local Area Network (WLAN) or WiFi) [31, 32].

The availability of occupant information provide an opportunity to quantify its contribution towards bridging the performance gap more robustly. Specifically, the measurements provides a means to empirically test the impact that various spatial resolutions of occupancy information have in reducing the discrepancies between simulation predictions and real measurements. For instance, using post-occupancy surveys to quantify OB, Yu, Du, and Pan [33] showed that the prediction accuracy of the energy model could be improved by integrating the survey results into the simulation model. Sangogboye [34] showed that using higher resolution occupancy data does not improve the accuracy of the energy model that was previously calibrated on lower resolution data. Using data from 16 single occupied private offices, O'Brien et al. [35] concluded that modeling occupancy from aggregated data tends to suppress inter-occupant diversities. The authors argue that although the high-level metrics showed that there is no strong evidence suggesting the suppression of inter-occupant diversities, occupancy profiles generated from aggregated data do not contain the same level of diversities observed in individual occupant profile.

1.4. Aims and objectives

Although the characterization of OB's impact on BPS is not new, a forward or classical modeling approach is typically employed, with most studies focusing on the modeling methodology of occupants and its resulting impact on BPS. It is also not evident from existing literature if standardized profiles can be tuned to provide models that are sufficient for predicting building energy usage. If standardized profiles are not enough, at what spatial resolution should occupant information be included in BPS to reduce the gap between simulated and measured energy use in buildings given an adequate calibration procedure? Monitoring occupancy at high spatial resolution (i.e., for a large number of zones) is an expensive endeavor, and there is a need to balance practicality with accuracy.

In this study, we employ an inverse empirical approach to quantify the effect of including occupant information on BPS predictive performance. Since simulation predictions are influenced by many known and unknown factors [36], Bayesian calibration is used for uncertainty quantification and to construct prediction intervals (PIs). The purpose of modeling and quantifying uncertainties is to robustly support any claims about the accuracy of the simulation predictions. Therefore, the objectives of this paper are:

- To evaluate the impact of including different spatial resolutions of occupancy information on model predictive performance.
- To elucidate the impact of base loads on predictive performance. Specifically, we would like to evaluate the improvements in predictive performance if the base loads of standardized profiles were calibrated.
- To propose a quantitative measure for the evaluation of simulation prediction intervals against measured data. Current literature does not offer a suitable metric to assess the quality (length and coverage) of the prediction intervals (PIs) quantitatively. Mean CVRMSE is often used for

the evaluation following ASHRAE Guideline 14 [37], which diminishes the purpose of constructing PIs in the first place [38].

2. Method

A combination of data acquisition/generation, modeling, and calibration will be used to quantify the effect of occupancy data towards match building energy simulation models to measured data. As illustrated in Figure 1, the framework used for the evaluation of different spatial resolutions of occupancy data on the efficacy of the calibration can be summarized as:

1. Acquire occupant count information, total building energy consumption data, and the corresponding weather data.
2. Create occupant information at different spatial resolution.
3. Calibrate building energy model with different spatial resolution of occupant information.
4. Evaluate and compare "calibrated" model performance.

2.1. Bayesian Calibration and meta-modeling

The impact that the availability of different spatial resolutions of occupant presence information would have on the predictive performance of the building energy model is evaluated within a Bayesian calibration framework. The motivation behind a Bayesian approach is to construct prediction intervals and quantify the uncertainties associated with the predictions of the realizations. The pioneering work by Kennedy and O'Hagan [39] laid the foundation for Bayesian calibration that explicitly models uncertainty in model inputs, the discrepancy between the simulator and the actual physical system, and observation errors (Equation 1).

$$y(x) = \eta(x, t) + \delta(x) + \epsilon(x) \tag{1}$$

where, $y(x)$ is the observed field measurement, $\eta(x, t)$ is the output of the building energy simulation given observable inputs x and unknown calibration

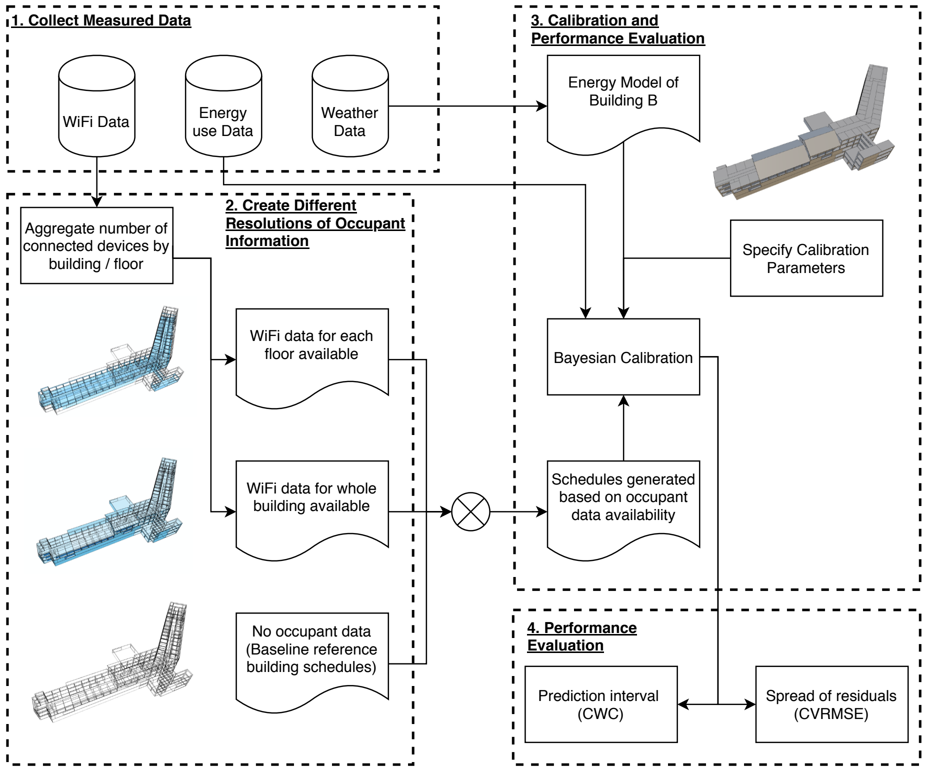


Figure 1: Framework for using real data to evaluate the impact of occupant presence on building energy simulation. Steps include (1) data acquisition; (2) using WiFi data as a proxy for occupant presence, create different resolution of occupant information; (3) Apply Bayesian calibration; and (4) Evaluate and compare the efficacy of the calibration given different spatial resolution of occupant information.

parameters t, $\delta(x)$ is the model bias or inadequacy or discrepancy, and $\epsilon(x)$ (assumed to be i.i.d and normally distributed) is used to model observation errors. The purpose of including the discrepancy term is to find the posterior distribution representative of the true but unknown values of the calibration parameters t. By incorporating model inadequacy δ, we believe that the calibration quality would improve since the model would better represent the actual physical system. Details on the implementation of Bayesian calibration for building energy simulation can be found in Chong and Menberg [27].

Since the iterative calibration process can be computationally intensive, a

Gaussian process (GP) emulator or metamodel is used to emulate the energy model and combine measured data with simulation data [40]. We use a GP metamodel because it has been shown to provide the highest accuracy compared to other commonly used statistical models despite its longer run-time [41]. A detailed description of the GP covariance function for $\eta(x, t)$ and $\delta(x)$ can be found in [42]. Maximin Latin hypercube sampling [43] was used to determine the different values of calibration parameters that would be used for the construction of the GP metamodel. Hamiltonian Monte Carlo (HMC), a Markov chain Monte Carlo (MCMC) method, is used to sample from the posterior probability distributions for more efficient sampling and better convergence [44, 45]. Gelman Rubin statistics ($\hat{R}$ within 1 ± 0.1) and trace plots of multiple MCMC chains were used to ensure adequate convergence to a common stationary distribution.

2.2. Calibrating load profiles/schedules

Internal loads refers to occupants, equipment (plug and process), and lighting loads. In this study, we quantify the effects on the model's predictive performance when the schedule base load fraction is modeled as a calibration parameter. Calibrating the schedule base load fraction increases the degrees of freedom for matching the simulation predictions to the measured data. Base load fraction here refers to the minimum schedule fraction. However, we do not model every hour value as a calibration parameter because calibrating too many parameters results in an ill-posed inverse problem. This is due to overparameterization that could lead to issues of identifiability [42]. Also, simpler models generalize better. More calibration parameters mean more complex models that tend to over-fit the measured data.

Figure 2 shows an illustration of varying the base load fraction of the ASHRAE 90.1 [15] equipment schedule while keeping the schedule's shape. We do this by taking advantage of the `Energy Management System` feature in EnergyPlus to modify and scale the schedule value during simulation runtime dynamically. Algorithm 1 shows the pseudocode for setting and scaling the equipment schedule fraction based on occupant schedule fraction and the equipment base fraction. At every simulation timestep t, the equipment schedule value $EQUIP_t$ is set equal to the calibration parameter X (base load fraction) when the building is not in operation. During operating hours, $EQUIP_t$ is set equal to the occupant schedule fraction OCC_t and scaled within the range $[X, 1]$.

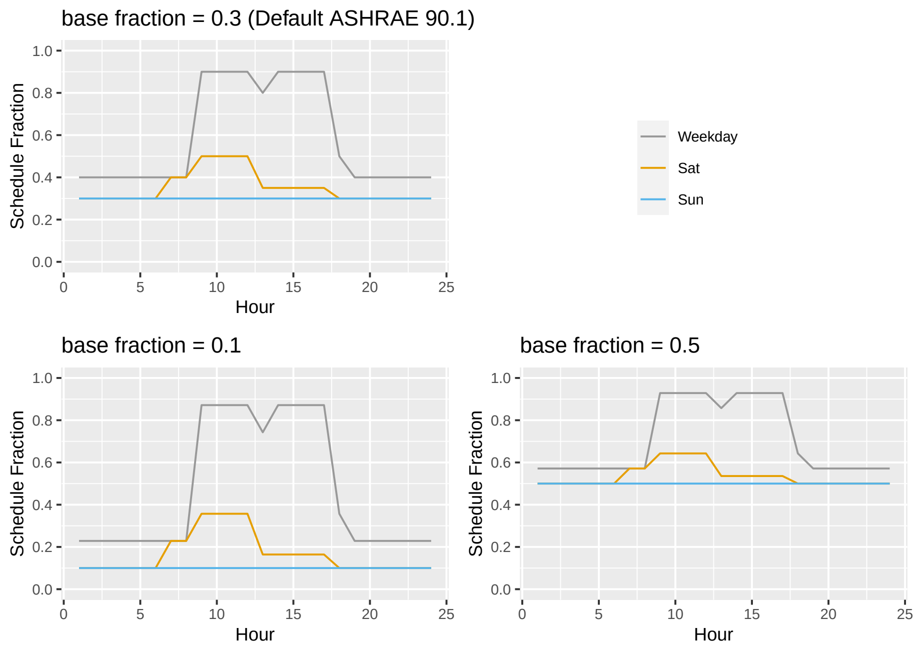


Figure 2: Modifying the base fraction of the load profile/schedule. Top plot shows the default ASHRAE 90.1 equipment (plug and process) schedule with base fraction of 0.3 (minimum schedule value). Bottom plot shows the same schedule re-scaled with base fraction of 0.1 and 0.5 respective.

Algorithm 1: Pseudocode for modifying and scaling the equipment schedule based on occupant information and equipment base fraction

```
X = equipment base fraction;
EQUIP = equipment schedule;
OCC = occupancy schedule;
OCC_min = minimum occupancy schedule fraction;
OCC_max = maximum occupancy schedule fraction;
for every simulation timestep t do
    if building is not in operation then
        EQUIP_t = X;
    else
        EQUIP_t = (OCC_t − OCC_min)(1 − X)/(1 − OCC_min) + X;
    end
end
```

2.3. Performance evaluation

Fig. 3 shows the framework used to evaluate model performance. Firstly, the dataset is split into a training/calibration and testing dataset. Secondly, Bayesian calibration is applied to the training dataset. Thirdly, EnergyPlus simulations are run using samples from the posterior estimates obtained from the Bayesian calibration. Lastly, the performance of the "calibrated" EnergyPlus model is evaluated using the testing data. We use two hundred random samples (i.e., the training data) for the Bayesian calibration. All the remaining samples were used as a hold-out test dataset for assessing model performance (See Table 2). Since a good match between simulation predictions and measured data on the training dataset does not necessarily mean that a proper calibration has been carried out, the test dataset that was not used during the calibration is used to validate the model's performance.

Model performance is evaluated using two evaluation metrics, the Coverage width-based criterion (CWC) and the coefficient of Variation of the Root-Mean-Square Error (CV[RMSE]). Each metric provides a different measure of

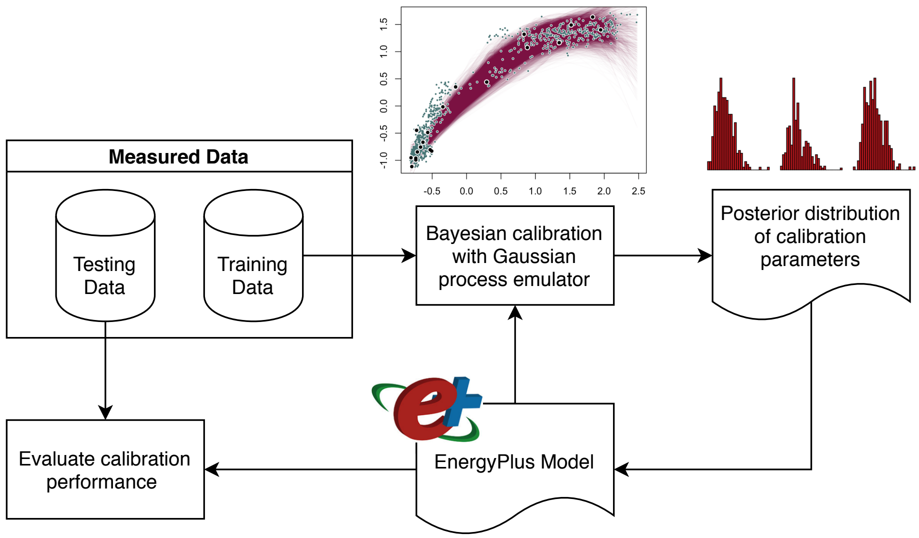


Figure 3: Framework for evaluating model performance. The posterior distributions of the EnergyPlus parameters generated from the Bayesian calibration is used as inputs to the model. The outputs of the model is then evaluated.

calibration effectiveness and is chosen to provide a robust evaluation of the uncertainties associated with the simulation predictions.

2.4. Coverage width-based criterion (CWC)

With the presence and accumulation of different sources of uncertainties [36], the construction of prediction intervals (PIs) for building energy simulation have often been proposed in literature. PIs are often evaluated based on their coverage probability without any discussion on how wide the intervals are. Put differently, studies often looked at whether measurements fall within the PIs. However, coverage probability by itself is not a good measure because a very high coverage probability can easily be achieved with PIs that have a broad range (i.e., a very small and large lower and upper bound respectively). PIs that are too wide are not useful in practice because they convey little information about the variations in the measurements. Therefore, evaluation of PIs based on coverage alone is subjective and can lead to misleading results [46].

In this study, we use the coverage width-based criterion (CWC) (eq. 2) [47, 48] to evaluate the PIs. CWC assesses the quality of the PIs based on both their coverage and their width through a combination of the Prediction Interval Coverage Probability (PICP) and the Prediction Interval Normalized Mean Width (PINMW) respectively. PICP (eq. 3) measures number of measurements that fall within the PIs while PINMW (eq. **??**) provides an indication of the normalized average width of the PIs. Narrow PIs are more informative about measurement variability. However, PIs that are too narrow may result in measurements falling outside the PIs. Therefore, using CWC provides an evaluation of the PIs from these two conflicting viewpoints.

$$CWC = PINMW + \gamma(PICP)e^{-\eta(PICP-\mu)} \tag{2}$$

where $\gamma(PICP) = 0$ when $PICP \geq \mu$ and 1 otherwise. μ is the nominal confidence level and its value can be determined based on the confidence level $(1-\alpha)\%$ associated with the PIs. η is a scaling factor for distinguishing PICP violations from μ. Together, μ and η are hyperparameters used to control the location and the amount of CWC jump. In this study, η and μ are set to 50 and 0.65 respectively.

$$PICP = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} c_i^{(\alpha)} \tag{3}$$

$$PINMW = \frac{1}{n_{test} \cdot R} \sum_{i=1}^{n_{test}} (U_i^{(\alpha)} - L_i^{(\alpha)})^2 \tag{4}$$

where n_{test} is the number of samples in the test dataset; if y_i denotes the ith observed value, then $c_i = 1$ if $y_i \in [L_i^{(\alpha)}, U_i^{(\alpha)}]$, otherwise $c_i = 0$; $L_i(\alpha)$ and $U_i^{(\alpha)}$ are the lower and upper bounds of the ith PI with a confidence level of $(1-\alpha)\%$, respectively; R is the range of the test dataset. Normalizing by R (eq. 4 allows us to compare the PIs generated from different datasets and calibration methods.

The intuition behind the CWC is to exponentially penalize violations of the preassigned where $PICP \leq \mu$, since it is a key feature that determines the correctness of the constructed PIs. When PICP is around μ, the CWC metric tries to compromise between informativeness (PINMW) and correctness (PICP) of the PIs.

2.4.1. CV(RMSE)

The coefficient of Variation (CV) of the Root-Mean-Square Error (RMSE) (eq. 5) is commonly used to assess how well the the calibrated energy simulation describes the measured data, and is used in this study to provide an indication of how well the mean of the posterior predictions matches the measured data. Relative to monthly and hourly calibration data, ASHRAE Guideline 14 [37] specifies a threshold of 15% and 30% respectively.With probabilistic predictions, prediction performance is evaluated using the mean and 95% confidence interval of the CV(RMSE) computed using the MCMC samples from the posterior predictions.

$$CV(RMSE) = 100 \times \frac{\sqrt{\sum_{i=1}^{n_{test}} (y_i - \hat{y_i})^2 \,/\, (n_{test} - 1)}}{\bar{y}} \tag{5}$$

$$\hat{y_i} = \frac{1}{m} \sum_{j=1}^{m} \hat{y}_{i,j} \tag{6}$$

where n_{test} is the number of samples in the test dataset; $\hat{y_i}$ denotes the mean of the ith predictions (eq. 6); $\bar{y}$ denotes the mean of the n_{test} measured values that forms the test dataset; m is the number of MCMC samples in the posterior predictions of $\hat{y_i}$.

3. Case study

3.1. Building description

The building case study is an actual mixed-use building (hereinafter referred to as Building B) located at the National University of Singapore in Singapore. It is a six-story building with a total floor area of 5,527m^2. The HVAC system is a VAV system served by central district water-cooled chillers. Given Singapore's tropical climate, no heating is required, and cooling is provided throughout the year to maintain thermal comfort.

Nine months of measured data at an hourly resolution from 1 Apr 2018 to 31 Dec 2018 was collected and consists of the following:

- Total building electricity energy consumption.
- WiFi connection counts for each floor of the building. WiFi connection counts have been shown in previous studies [29, 49] to be a suitable estimate of the hour to hour variations in the number of building occupants. Therefore, it is used in this study as an implicit estimate of occupancy profiles or schedules.
- Actual Meteorological Year (AMY) weather data from the Singapore Changi airport weather station (WMO #486980).

3.2. Virtual experiments

Using data from the case study building, four virtual experiments A, B, C, and D are defined to evaluate the impact of occupant presence on the calibration efficacy of building energy simulation and are summarized in Table 1 with descriptions as follows.

Case A Default ASHRAE 90.1 occupancy, lighting and equipment load schedules.

Case B Default ASHRAE 90.1 occupancy, lighting and equipment load schedules. Equipment base load fraction is modeled as an uncertain parameter (Fig. 2) that is calibrated against hourly whole building energy usage data.

Case C Default ASHRAE lighting schedule. Whole building aggregated occupant information is used to derive both building aggregated occupancy and equipment load schedules. Equipment base load schedule fraction is modeled as an uncertain parameter that is calibrated against hourly whole building energy usage data.

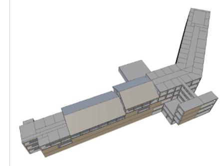
Case D Default ASHRAE lighting schedule. Floor aggregated occupant information is used to derive the corresponding occupancy and equipment load schedules for each floor. Equipment base load schedule fraction for each floor aggregated schedule is modeled as an uncertain parameter that is calibrated against hourly whole building energy usage data.

Table 1: Summary of experiments used to investigate the effect that different spatial resolution of occupant presence has on the calibration efficacy of building energy simulation.

Case	Occupant data source	Occupant data resolution	Calibrates equipment base load
A	ASHRAE 90.1	None	No
B	ASHRAE 90.1	None	Yes
C	WiFi	Aggregated by building	Yes
D	WiFi	Aggregated by floor	Yes

Table 2 summarizes the data, priors, inputs and output used for the Bayesian calibration. To ensure a fair comparison, each case was optimized by conducting a grid search of the Gaussian process hyperparameters on the training dataset and selecting the hyperparameters that gave the lowest CWC (eq. 2) values. The calibration is carried out against hourly building energy consumption data. Table 2 lists the boundary conditions, calibration parameters, GP hyperparameters, and the corresponding prior probability distributions used for the Bayesian calibration. To ensure that the diversity factors generated based on the WiFi connection counts are correctly applied, we sum the hourly total occupant count for the building and checked that they are the same across the different spatial resolutions.

Table 2: Data description, priors, inputs and output for Bayesian calibration using the real dataset (Building B).

	Description
Building	 Mixed-use building located in Singapore
Data collection period	1 Apr 2018 to 31 Dec 2018
Weather	Singapore Changi Airport WMO #486980 (AMY)
No. of samples	training: 200 testing: 6304
Observed output $y(x)$	Total building energy consumption (excluding plant side cooling consumption)
Observed Inputs x	Outdoor dry-bulb air temperature $[°C]$ Outdoor relative humidity [%] Direct solar radiation $[W/m^2]$ Occupant schedules $[-]$ (see Table 1)
Calibration Parameters $t^\dagger$	Occupant density $[m^2/person] \sim \mathcal{U}(15, 23)$ Lighting power density (LPD) $[W/m^2] \sim \mathcal{U}(3, 20)$ Equipment power density (EPD) $[W/m^2] \sim \mathcal{U}(3, 30)$ Base load ratio (EPD) $[-] \sim \mathcal{U}(0.05, 0.6)$
Gaussian process hyperparameters	$\lambda_\eta \sim Gamma(a = 10, b = 10)$ $\lambda_\delta \sim Gamma(a = 10, b = 0.1)$ $\rho^\eta, \rho^\delta \sim Beta(a = 1, b = x)$ $\lambda_\epsilon \sim Gamma(a = 10, b = y)$ $\text{argmin}_{(x,y)} CWC^\ddagger$ $x \in (0.1, 0.3, 0.5)$ and $y \in (0.01, 0.05, 0.1)$

† For case D (total number of occupants per floor is approximated using WiFi connection count data), the power density and base load of each floor is modeled as a random variable that is calibrated. For a five storey building, this means a total of ten calibration parameters for EPD and each corresponding base load. Note that we model occupant density as a calibration parameter. This is because, although WiFi data acts as a good proxy for occupant hourly variation/schedule, it is not a good estimate for actual occupant count. ‡ optimized by conducting a grid search on the training dataset and selecting the x and y values that gave the lowest CWC (eq. 2) values. A detailed explanation of the GP hyperparameters for Bayesian calibration can be found in Chong and Menberg [27].

4. Results

Table 3 summarizes the results of the four virtual experiments using the testing data. CWC and CV(RMSE) were computed to provide a quantitative assessment and comparison of the predictive performance at different resolution of occupant information with both synthetic and real data (see Table 1).

Table 3: Performance of prediction intervals for the eight case studies to 2 significant figures.

Metrics	Case			
	A	B	C	D
CV(RMSE)	37	29	24	26
CWC	9.7×10^6	1.3	0.16	0.20
PICP	0.33	0.65	0.67	0.71
PINMW	0.11	0.17	0.16	0.20

As illustrated in Figure 4, the quality of the prediction intervals improves when occupant data is included in the calibration. This is indicated by lower CWC and CV(RMSE) values in cases C and D relative to A and B. Specifically, compared to default ASHRAE 90.1 schedules (case A), including occupancy data (cases C and D) shows a 11% - 13% reduction in mean CV(RMSE) and an exponential improvement in CWC. The CWC measure (Eq. 2) is based on PICP (prediction coverage) and PINMW (prediction width). Its hyperparameters (η and μ) were chosen so that PIs with $PICP \leq 65\%$ are heavily penalized. The considerably improvements in the CWC measure is mainly brought about by an increase in prediction coverage (PICP). From Table 3, it can be observed that including occupant information increases PICP by more than 30% (compared to using default ASHRAE 90.1 schedules).

A comparison of the simulation PIs with the measured data reveals that with the default ASHRAE 90.1 schedules, the calibrated model is unable to capture the base loads. Figure 6 illustrates this observation using case A as an

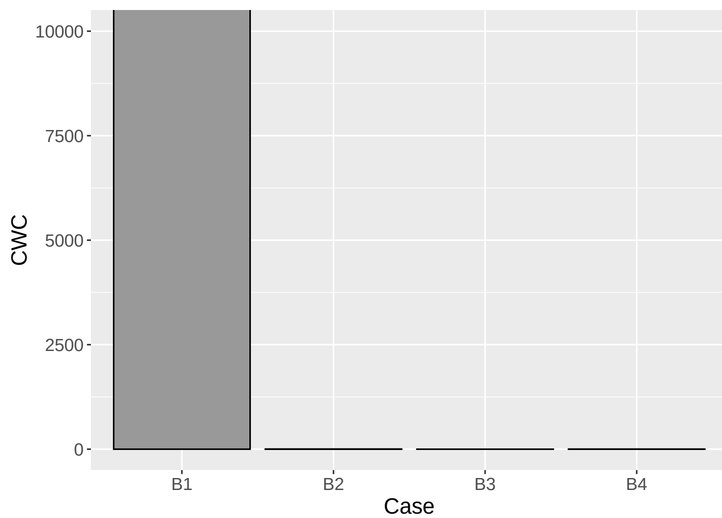


Figure 4: Coverage Width-based Criterion (CWC) values for the four cases A-D (described in Table 1)

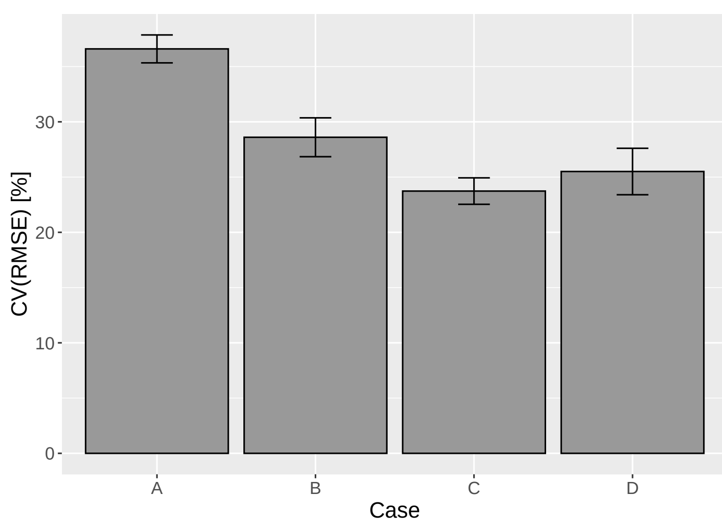


Figure 5: Coefficient of Variation of the Root-Mean-Square Error (CV[RMSE]) values for the four cases A-D (described in Table 1).

example. There are two distinct observations, (1) the measurements fall outside the PIs during non-operating hours (base load), and (2) a significant mismatch between the PIs and the measurement results if the building is assumed to be in operation when it is not. Evidently, a higher degree of freedom when tuning the ASHRAE 90.1 schedules and the correct assumptions concerning the building's operation is necessary. We test this hypothesis with case B where the base load schedule fraction is modeled as a calibration parameter (see Section 2.2 for the methodology).

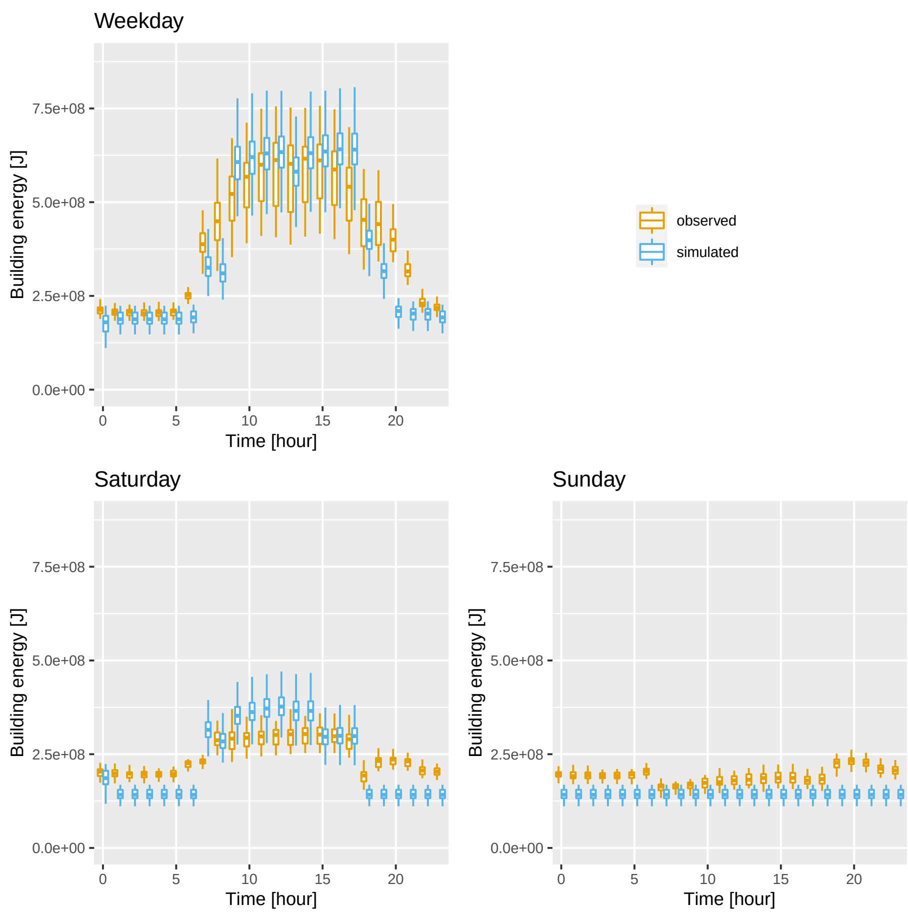


Figure 6: Weekdays, Saturday, and Sunday box-plots of simulation predictions (blue box-plots) for Case A that uses the default ASHRAE 90.1 schedules for the calibration against hourly building energy consumption measurements (orange box-plots).

By calibrating the base load schedule fraction, CWC values were substantially reduced (Figure 4) due to significant improvements in PI coverage of the measurements (approximately 30% increase in PICP as shown in Table 3). The mean CV(RMSE) were also reduced by 8% compared with case A (Figure 5). Notably, going from default ASHRAE 90.1 schedules (case A) to adding base load schedule fraction as a calibration parameter (case B) to including building aggregated occupancy data (case C), we observe that by modeling the base load fraction as a calibration parameter, the performance gap between including and not including occupancy data diminishes. Specifically, the CWC values are comparable when comparing cases B and C. Nonetheless, including building aggregated occupancy shows an additional 5% reductions in CV(RMSE) (Figure 5).

Providing floor aggregated occupancy (case D) does not improve the quality and accuracy of the simulation PIs. As shown in Figures 4 and 5, compared to case C, case D has a slightly higher CV(RMSE) and CWC. The deterioration in CWC is because the PIs for case D had a broader range on average (PINMW) while having comparable PICP compared to case C. This indicates that case D has comparatively higher uncertainties in its posterior predictions while having similar coverage of the measured data. A possible explanation for the worsened CV(RMSE) and CWC is that the diversity factors from occupancy data provided at the floor level do not add more information (as compared to building aggregated occupancy information) towards the prediction of total building energy consumption. Additionally, calibrating the power densities and base load schedule fraction of each floor may result in too many calibration parameters and a overly complex model.

Surprisingly, CV(RMSE) of case D is between that of cases B and C. Following the principle of parsimony, case B that does not rely on any occupant data and has fewer lesser calibration parameters might be preferred in scenarios where a CV(RMSE) of 29% is deemed acceptable.

5. Discussion

5.1. Comparing ASHRAE Schedule to using occupancy data

By substituting ASHRAE 90.1 reference schedules with building aggregated occupancy data, the deviation between predicted energy consumption and measured data were reduced by 13%. The improvements in prediction accuracy comes as no surprise since occupancy diversity factors was shown to differ by as much as 46% in average day profile peaks for private offices and about 12% reduction for open plan office spaces as compared to ASHRAE 90.1 reference schedules [16]. Variations in occupant related loads and schedules were also shown to have an significant impact on total building predicted energy usage [10]. Using an actual building, we showed that even with an adequate calibration methodology, CV(RMSE) stayed above the hourly threshold of 30% set by ASHRAE Guideline 14 [37] (Figure **??**). By including occupancy information, this deviation was reduced to 29% and within ASHRAE Guideline 14 [37] definition of a calibrated model.

Compared to the existing literature on occupant behavior, a noticeable difference in this study lies in applying Bayesian calibration to quantify the uncertainties in the simulation predictions. Additionally, the quality of the constructed prediction intervals (PIs) were evaluated using the simple coverage width-based criterion (CWC) that evaluates the PIs for its correctness (coverage of PIs) and its informativeness (width of PIs). As shown in Figure **??**, including occupancy information exponentially improves the quality of the constructed prediction intervals (PIs). Specifically, the PIs from a calibrated energy model where the schedules were based on occupancy data were more theoretically correct with more than 30% of the measured data being covered by the constructed PIs. Interestingly, with case A, it was shown that a CV(RMSE) of 37% can be achieved even though the constructed PIs only covered about 30% of the measured data. This observation provides evidence that despite calibrating for internal load (people, lighting, and equipment) densities, using fixed *a priori* reference schedules may result in simulation predictions in which the correctness of the constructed PIs is questionable.

5.2. Modifying ASHRAE schedule

Although we show that using ASHRAE reference schedules provide PIs with inadequate coverage of measured building energy usage, the question is whether these reference schedules can be adjusted to ensure sufficient accuracy and correctness. Accordingly, we show that increasing the calibration degree of freedom by modeling of schedule base load fraction as a calibration parameter reduces the performance gap with comparable correctness in the constructed PIs than if occupancy data was included. However, the mean CV(RMSE) remains 5% larger. This suggests that if the peak and base loads can reasonably estimated, the ASHRAE reference schedules might not be as detrimental as purported when used in BPS for predicting building energy usage.

To date, fixed *a priori* reference schedules represent the lowest level of complexity [14]. Schedules are also easy to include with implementation-ready interfaces in existing energy simulation software. Comparatively, more complex probabilistic and agent-based models have been proposed to better model occupant presence and their interaction with various energy-related components in a building [2]. These models in an attempt to better represent occupancy in BPS often requires significant amount of information in reality, which may not always be available especially during the design stage. Consequently, prediction performance may decrease if the uncertainties from estimating the input parameters exceeds the benefits of a reduced model inadequacy or bias resulting from an increase in model complexity [26]. Furthermore, simple models often generalize better and are easier to implement, making them more suitable during design.

The question then remains whether a reference schedule with its base and peak loads adjusted serves as a good enough abstraction of actual occupant presence and their interaction with the building systems. Compared to the more complex probabilistic and agent-based occupancy models, would adding additional degrees of freedom to the reference schedules provide better generality and still achieve the predictive performance needed to meet the simulation objectives? In future work, investigating this research question might prove important.

5.3. Model complexity, inputs, outputs, and simulation objectives

Fig. 7 represents the trade-offs between model bias and parameter uncertainty, drawing from the results of this study; ongoing discussions to develop parsimonious building energy models [26, 14, 50]; and the relevant literature that delves into the effects on model performance with varying model complexity, data quality, and the simulation objectives [51, 52, 53, 54].

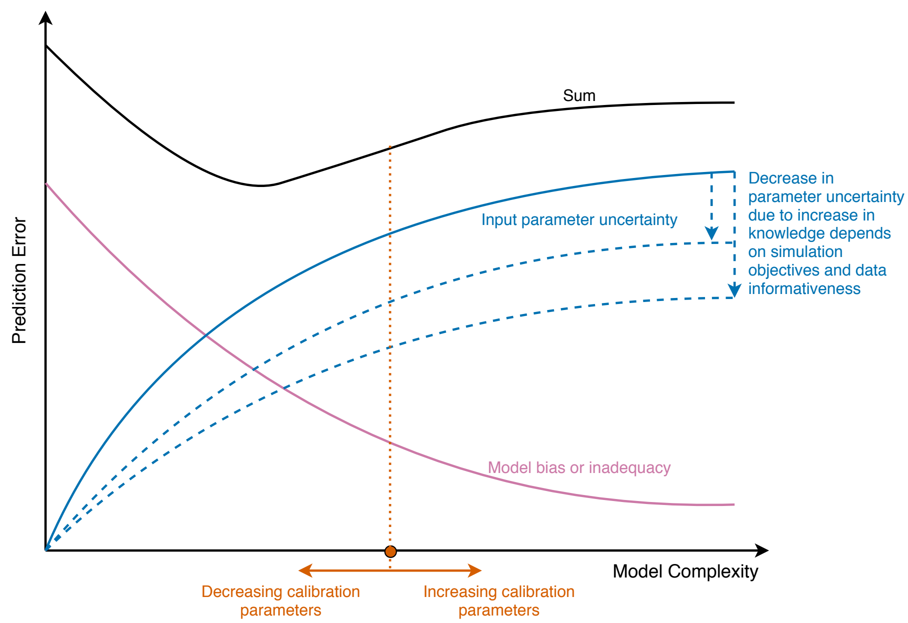


Figure 7: Trade-offs between parameter uncertainty and model inadequacy with increasing model complexity, and the corresponding effects due to the simulation objectives, model inputs and outputs, and calibration parameters.

Increasing the resolution from building aggregated occupancy data to floor aggregated occupancy data showed a 2% increase in prediction error. A recent study by Sangogboye et al. [34] reported similar findings of an increase in prediction error from 19.72% to 21.03% when switching from average building aggregated occupancy data to detailed zonal level occupancy data. Additionally, we showed in this study that increasing the spatial resolution increased the range of the posterior PIs on average, indicating an increase in prediction uncertainties. This is because using higher resolution occupancy data increases the number of model parameters and thus the model's complexity as compared to an abstracted version where similar parameters are lumped into a single building aggregated parameter. An example is modeling the lighting power densities for each space and subspace compared to a simplified approach that models the building aggregated lighting power density. Depending on the outputs or responses that the simulation model is calibrated against, increasing the number of calibration parameters can result in issues of identifiability as a result of overparameterization [27].

The findings from this study suggest that although complex models provide a better representation of the actual physical building systems and subsystems, they may not be useful if a comprehensive dataset is not available to constrain each pathway. This is because the model's performance depends on (1) model complexity, (2) simulation objectives, and (3) data informativeness. A more accurate representation of building systems and sub-systems requires more knowledge that could come from informative data streams, detailed drawings, and specifications because of the increasing number of model parameters. Additional complexity inadvertently leads to an increase in the number of uncertain parameters that need to be calibrated against an often limited amount of data streams. Therefore, it is crucial that modelers identify the appropriate level of complexity for a given dataset and simulation objective (question of interest). As suggested by [55], simulation is no longer the art of performing high fidelity simulations but rather performing the right type of virtual experiment with the right model. The effects of model complexity and structure, simulation objectives, and data informativeness on building performance simulation remain unanswered at present and is an important issue for future research

6. Conclusion

The present study was designed to determine the effect of occupancy data on the building energy simulation model's predictive performance. To robustly support claims about improvements in predictive performance, Bayesian calibration is used to construct prediction intervals (PIs) and quantify any associated uncertainties. We also propose using the coverage width-based criterion to better evaluate the quality of the PIs.

The more obvious finding to emerge from this study is that compared to ASHRAE 90.1 reference schedules, including occupancy information (in the form of hourly profiles) improves the quality and accuracy of the PIs.

One of the more significant findings revealed in this study is that increasing the calibration degree of freedom by calibrating the schedule base load fraction reduces the gap between using ASHRAE reference schedules and occupancy information substantially. The finding suggests that with a reasonable estimation of the peak and base loads during design, the ASHRAE reference schedules might not be as detrimental as purported when the simulation objective is to predict total building energy usage.

The second significant finding was that a higher spatial resolution of occupancy data might result in poorer predictions with larger uncertainties of total building energy usage than whole building aggregated occupancy data. The finding supports the idea that additional model complexity leads to an increase in parameter uncertainty. If data that is informative about the simulation objective is not available to constrain each pathway, it would inadvertently lead to an increase in overall uncertainty despite a reduction in model bias or inadequacy arising from more detailed modeling.

If applied to more buildings, the outcome of this study would provide a basis for quantifying occupancy uncertainty during design, thus preempting the performance gap through better quantification of the variability in the predictions.

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