FROM COMPLEXITY TO SCALABILITY: SIMPLIFYING BUILDING ENERGY MODELS FOR WIDER ADOPTION

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ABSTRACT

Building energy modelling (BEM) can help accelerate the net zero built environment by assisting with the design, implementation, and evaluation of energy-related policies. For BEM to be actionable, model accuracy must be validated. Unlike newer buildings, older buildings often lack mechanisms to generate detailed data. BEM can also be labour-intensive, limiting its accessibility. This study explores the balance between modelling accuracy and complexity by examining the impact of various data inputs and modelling methodologies for a case study of an older building at the University of Oxford. A white-box energy model is created on DesignBuilder to reflect the building's current energy performance. Data collection includes documentation review, site audits, online surveys, Wi-Fi-based occupancy monitoring, and in-situ U-value measurements. The model is calibrated against monthly energy usage. Modelling inputs are gradually simplified to quantify changes in accuracy and sensitivity, and reduction in model complexity. This study demonstrates that well-calibrated, yet simplified energy models can be an accessible and time-efficient tool for informing policy decisions aimed at achieving a net zero built environment, even when buildings are old and data is limited.

Keywords: building energy modelling; calibration accuracy; model simplification; data resolution; data quality.

INTRODUCTION

Energy demand and efficiency policies will be crucial to meet the Paris Agreement requirements (Süsser et al., 2021), especially for the building sector, which accounts for 30% of global energy demand (Cheng et al., 2024). Building Energy Modelling (BEM) uses computational models to represent the physical characteristics and operations of a building (Hong et al., 2018). BEM can help design and validate energy conservation measures (ECMs) policies, and ensure compliance with building standards (Coakley et al., 2014). Despite its widespread use in building design, BEM is less common for existing buildings (Hong et al., 2018). Considering 90% of current buildings will still be in use by 2050 (Maduta et al., 2022), extending the use of BEM to existing buildings, especially with poor data access, can help accelerate their decarbonisation.

The quality of BEM outputs, and hence its utility for policy making, depends on the quality and availability of the input data (Coakley et al., 2014). While modern buildings with Building Management Systems (BMS) may provide high-resolution data, older buildings often lack mechanisms to generate such data (Chong, Gu, et al., 2021). Additionally, BEM can be complex and time-consuming. Some methods, such as black- or grey-box modelling use data-driven approaches which accelerate development times but lack explicit links between model inputs and building parameters, making it difficult to assess ECM impacts (Coakley et al., 2014). White-box modelling adopts a 'bottom-up' approach to provide a better understanding of building behaviour but requires extensive input data and modelling efforts (Li et al., 2021). Simpler modelling and data collection methods which maintain confidence and accuracy are needed.

Previous research has focused on the effect of single model parameters on simulated energy consumption (Chong, Augenbroe, et al., 2021; Johari et al., 2022; Korolija et al., 2011) and temporal resolutions of input data (Khayatian et al., 2022; Kristensen et al., 2017), without investigating data sourcing and accessibility. Cheng et al. (2024) explored the balance between information-gathering efforts and model reliability on a single zone test bed, limiting applicability to the whole building level. Kong et al. (2023) analysed at the whole building level but did not examine the model bias, crucial to understanding if approaches are over- or under-predicting energy results. This paper aims to build on previous research to answer the following questions:

1. What types of data are essential for an accurate yet simplified BEM?
2. How do information-gathering and modelling simplifications affect model accuracy?
3. How do these simplifications reduce modelling efforts and simulation memory usage?
4. What is the sensitivity of different input parameters on simulated energy consumption?

These questions are investigated using the case study of a 1989 Oxford University faculty building: the Department of Pharmacology. This building is a good example of a typical non-domestic structure of above-average age that has been in continuous use for decades. The paper introduces the BEM methodology and simplification steps. Results are then presented and critically discussed for key recommendations and future work.

METHOD

This study employs a white-box modelling approach with iterative manual calibration for precise adjustments and reduced uncertainty (Coakley et al., 2014). An initial detailed model of the case study building is created on DesignBuilder (DB), the graphical user interface for the simulation engine EnergyPlus. The input parameters and modelling methods are then gradually simplified to evaluate their impact on accuracy, assessed using the coefficient of variation of the root mean square error (CV(RMSE)) and the normalised mean bias error (NMBE) functions, as recommended by ASHRAE Guidelines 14-2014 (ASHRAE, 2014). These functions quantify how well a model fits real data and identify overall model bias (Coakley et al., 2014). Average zone temperatures and relative humidities (RH) are also verified to ensure simulated indoor environmental conditions are accurate (Derakhti et al., 2022). Additionally, a sensitivity analysis is conducted to identify the most influential input parameters on energy consumption and calibration accuracy (Derakhti et al., 2022). Finally, each model's simulation memory usage and estimated reduction in data collection and modelling efforts are quantified.

Case Study Overview

The building dates from 1989 and includes laboratories (labs), offices, and common areas. Heating is provided by three gas-condensing boilers and a combined heat and power (CHP) generator. Most spaces are equipped with radiators or radiant panels. Labs and some offices have variable refrigerant flow (VRF) air-conditioning (AC) units or fan coil units. The building also contains 11 close-control spaces with monitored temperature and RH, served by an air handling unit (AHU).

Baseline Model Data Collection

The baseline (BASE) model is shown in Figure 1. The input parameters used for modelling are summarised in Table 1. U-values for external walls and windows are obtained via 72-hour in-situ measurements using the wireless U-value gOMS II measurement system (greenTEG, 2024), complying with ISO 9869-1:2014 (ISO, 2014). Occupancy densities and schedules are based on Wi-Fi hourly connections over a 3-month period, extrapolated for the entire year. Lighting information is sourced from recent LED replacement floor drawings, with most lights having passive infrared (PIR) sensors. A 6-hour site audit provided zone heating, ventilation, and air-conditioning (HVAC) and unregulated loads (UL) equipment schedules, supplemented by an online lab survey. An actual meteorological year (AMY) 2023 Oxford weather file is sourced from Oikolab, which provides historical datasets from national weather agencies (Oikolab, 2023).

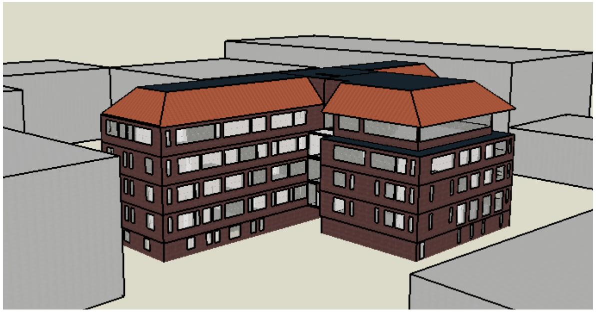

Figure 1: The DesignBuilder BASE model consists of 329 zones.

Metered electricity and gas data for 2023 are collected via an online dashboard with sub-hourly resolution. The building has one gas meter and several electricity submeters separating usage between CHP production, heating controls, AHU, and general power use (lighting, AC, and UL). Data gaps in October and December for AHU and general power use meters are filled using historical data proxies. These gaps account for 20 days' worth of electricity demand in total. Finally, despite the presence of a BMS in the building, it is obsolete and provides no valuable information for this study.

Baseline Model Calibration

The BASE model is manually calibrated using monthly 2023 metered electricity and gas data. Calibration for heating, CHP, and AHU uses sub-metered data directly, allowing for precise adjustments of these systems. The calibration of general power use, which combines lighting, AC, and UL, requires a more nuanced approach due to the uncertainty primarily stemming from the UL contribution. To address this, an iterative adjustment process is employed where the UL contribution is systematically varied and the model re-run until the simulated total general power use closely aligns with the measured data. The calibration accuracy is validated using the CV(RMSE) and NMBE functions and by verifying daily average zone temperatures and close-control zone RHs. Based on these validation results, fine-tuning of model parameters are performed to improve alignment with measured data while maintaining physical realism, ensuring that the BASE model accurately represents the building's energy performance across all major systems.

Model Simplification Process and Validation

After validating the BASE model calibration, simplified models are created to simulate scenarios with limited data and time. Each model is derived by modifying one parameter at a time to avoid increased equifinality of the simulation models (Zhan et al., 2023). Input parameters are carefully selected to maintain the BEM's utility for further ECM testing. The simplified models are summarised in Table 2.

Table 1: Summary of input parameters sources and modelling resolutions for the BASE model.

Category	Input parameter description	Input parameter source	Resolution
Fabric	External walls and windows - U-values	U-value measurement kit	Building
	Other fabric elements - U-values	Building documentation and DB database	Building
Occupancy	Density - number of people per zone	Wi-Fi data	Zone
	Schedule		Zone
Lighting	Power density	LED drawings	Zone
	Operating schedule	PIR-based - follows occupancy	Zone
Domestic hot water (DHW)	Hot water daily usage	Monthly water bills and lab audits	Zone
UL	Power density	Lab surveys and site audit	Zone
	Operating schedule		Zone
HVAC	Zone and plant equipment and technical specifications	HVAC datasheets, building documentation, site audit, and discussion with building users	Zone
	Operating schedules		Zone
	Setpoints (temperature, RH)		Zone
Geometry	Layout	Architectural drawings	Zone
Weather data	Weather file (EPW)	AMY Oxford 2023 (Oikolab)	Building
Meter data	Monthly electricity and gas consumption	Energy online dashboard	Building

Table 2: Summary of input parameters and modelling simplifications for each model.

Category	Model	Simplification description	Input parameters under study
Fabric	FAB1	No U-value measurement: based on architectural drawings and DB	U-value
	FAB2	No architectural drawings: based on old construction regulations (NCM, 2024)	
Occupancy	OCC	No Wi-Fi data: based on observed room capacities and activity patterns	Occupancy density & schedule
Lighting	LIT	No LED drawings: based on CIBSE LED standards (CIBSE, 2012)	Lighting power density
DHW	DHW	No monthly water bills: based on ASHRAE hot water usage (ASHRAE, 2007)	DHW daily usage
UL	POW1	No lab surveys: based on site audit and lab equipment schedule assumptions	UL operating schedule
	POW2	No site audit: based on CIBSE standard power densities (CIBSE, 2012)	UL power density
HVAC	HVC1	No site audit: assume all offices and common spaces have a radiator, and labs have a radiator and a VRF unit. Close-control zones remain unchanged	HVAC zone equipment
	HVC2	Assume all zones have a radiator and a VRF unit, with uniform setpoints. Close-control zones remain unchanged	HVAC zone equipment
	HVC3	Assume all zones have a radiator and a VRF unit, with uniform setpoints, including close-control zones	HVAC zone equipment
	PLANT	No HVAC loop drawings: loop flow rates are set as 'Autosized' on DB	HVAC loops flow rates
Geometry	ZON1	Simplified layout while still maintaining same number of zones	Zone geometry
	ZON2	Merged neighbouring zones of similar activities	
	FLOOR	Model each floor as one single zone	
	BUILD	Model the building as one single zone	
Weather data	TMY1	No AMY weather file: use typical meteorological year (TMY) Heathrow weather file (84 km from Oxford)	Weather file (EPW file)
	TMY2	No AMY weather file: use TMY Gatwick weather file (140 km from Oxford)	
Meter data	MET	No meter data pre-processing	Monthly meter readings

The PLANT model only involves modifying HVAC loop flow rates as power ratings and efficiencies, sourced from building documentation, are considered essential and therefore not simplified. Additionally, the ZON1 model assumes less time spent on creating a detailed 3D model. Zones are simplified into basic cubes, ignoring minor layout details. Finally, the MET model does not involve changing any inputs in the DB model but rather compares the BASE model's simulated energy to the raw meter data without pre-processing.

Sensitivity Analysis

A sensitivity analysis is conducted to understand the impact of each input parameter on simulated energy consumption and consequently, model calibration. This helps identify essential data sources and modelling methods. The influence of each parameter is quantified using the 'influence coefficient' (IC) calculated using Equation (1) (Westphal & Lamberts, 2005).

$$IC = \left| \frac{\Delta OP \div OP_B}{\Delta IP \div IP_B} \right| \quad (1)$$

Where ΔOP and ΔIP are the changes in output (energy) and input respectively, and OP_B and IP_B are the BASE model outputs and inputs respectively. For consistent comparison, the IC is taken as an absolute value. Table 3 summarises the base input and new input data for each model.

Table 3: Summary of BASE and new models' data inputs.

Model	Model input	BASE input	Unit
FAB1 – ext. walls	0.405	0.49	W/m2K
FAB1 - windows	1.844	2.158	
FAB2 – ext. walls	0.45	0.49	
FAB2 - windows	2.664	2.158	
OCC	500	625	People
LIT	10	7	W/m2 (average)
DHW	2.1	4	L/m2/day
POW1	45	70	h (weekly operating hours)
POW2	25	34.5	W/m2 (average)
HVC1	214	140	Radiators and VRF units
HVC2	280		
HVC3	302		
PLANT – water	0.002	0.12	m3/s
PLANT – air	33	10	m3/s
ZON1	241	329	Zones
ZON2	151		
FLOOR	5		
BUILD	1		
TMY1	84	10	Distance from Oxford (km)
TMY2	140		

For each simplified model, two ICs are computed, one based on gas output and the other on electricity output. The higher the IC, the more sensitive the simulated energy is to the input parameter.

RESULTS AND DISCUSSION

Model Accuracy

Figures 2 shows the CV(RMSE) and NMBE results for each model, reordered for clarity. Validated simplifications include using standard databases for DHW daily usage and lighting power density (DHW, LIT). Simplified zone geometry modelling is also acceptable (ZON1, ZON2), but further merging of zones invalidates the models (FLOOR, BUILD). Raftery et al. (2011) reached similar conclusions, emphasising the need for adequate zone-typing (i.e. only merging zones of similar activities and HVAC configurations). Additionally, conducting extensive site audits for detailed zone HVAC equipment may not be necessary (HVC1, HVC2), but understanding zone thermal conditioning types is crucial (HVC3). Better accuracy is needed for HVAC plant equipment (PLANT), echoing findings by Ahn et al. (2014) regarding the reliability issues with 'Autosized' parameters in EnergyPlus. U-value measurements can be costly, yet they only reduce the average NMBE by 0.7% in this case study. If available, alternative construction material information sources can be used (FAB1, FAB2).

Similarly, collecting Wi-Fi data can be an intrusive process and only reduces the average NMBE by 1.1%. Considering the lab-centric nature of the building, occupancy has a smaller impact on energy consumption. Other simplified methods of occupancy data collection can thus be employed (OCC). However, other building types such as offices may require more detailed occupancy data (Peinturier & Wallom, 2024). Additionally, conducting detailed lab surveys to understand UL usage patterns can be avoided (POW1). But understanding specific equipment power usage is crucial, especially in UL-heavy buildings (POW2). The TMY1 and TMY2 weather files passed validation but near limits. The infrequent update of TMY files raises the risk of underestimating current-year weather impacts (Siu & Liao, 2020). Using an AMY file from a nearby weather station is preferable. Finally, the MET model is close to the CV(RMSE) limit, indicating the significance of accurate meter data for calibration validation.

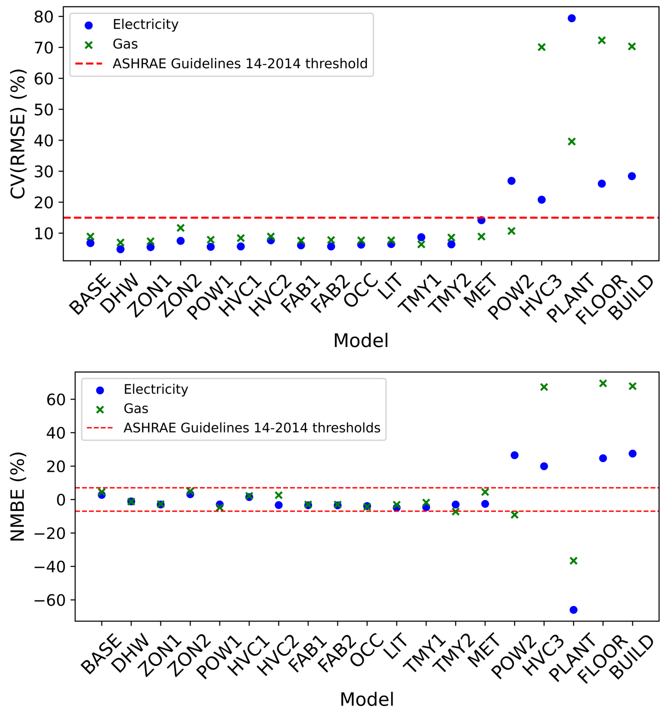

Figure 2: Resulting CV(RMSE)s (top) and NMBEs (bottom) show that most simplifications keep the models within the recommended thresholds.

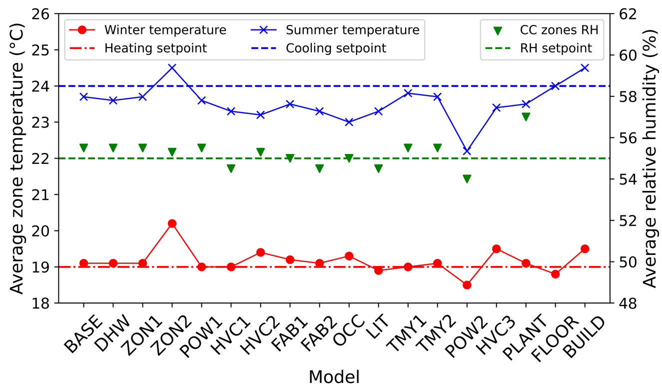

Figure 3: Average zone temperatures and close-control (CC) zone relative humidities show that most simplified models continue to uphold reasonable thermal comfort setpoints.

Figure 3 summarises average zone temperatures and close-control zone RHs. ZON2, POW2 and BUILD have the largest temperature differences, but ranges remain acceptable. The close-control zones for all models fall approximately within the RH setpoint (55%) except the PLANT model, highlighting the importance of well-defined HVAC plant equipment for space conditioning.

Sensitivity Analysis

Figure 4 summarises the ICs for each model's electricity and gas simulated demand, reordered for clarity. Simulated electricity demand is most affected by UL and lighting power densities (POW2, LIT), and plant HVAC parameter changes (PLANT). This is due to the significant share of lights and lab equipment in the building and the heavy reliance of HVAC controls on electricity. UL schedules have less impact (POW1), indicating the higher influence of constant-power loads like freezers and fridges. The FLOOR and BUILD models show a high correlation between space modelling and gas usage, highlighting the importance of adequate zone-typing for thermal modelling. The HVC3 gas IC emphasises the need to account for close-control thermal spaces if these exist. Overall, systems-related factors appear to have the greatest impact on sensitivities, while human interactions play a smaller role. This reflects the building's purpose, with equipment-driven loads dominating over human-related operations. Sensitivity findings may differ across building types, depending on the relative influence of occupancy and systems-related factors in each case.

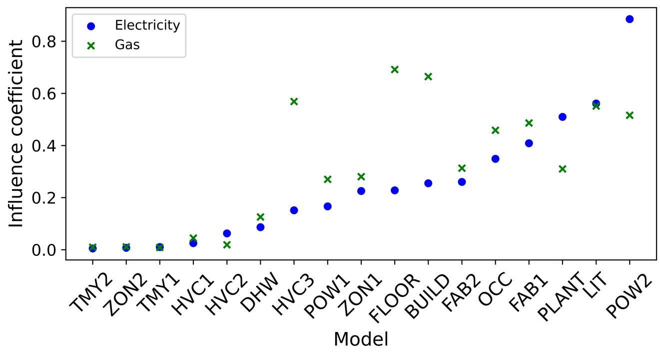

Figure 4: Resulting model influence coefficients show that energy demand is most affected by unregulated loads, plant HVAC, and space modelling changes.

Simulation Memory Usage and Ease of Modelling

Figure 5 summarises simulation memory usages. The FLOOR and BUILD models use the least memory but failed calibration. ZON1 and ZON2 reduce memory usage and passed calibration. HVC2 and HVC3 has the highest memory usage due to the modelling of more HVAC zone equipment than the BASE model. These results indicate that zone geometry and HVAC modelling have the biggest impact on memory usage, serving as indicators for efficient modelling.

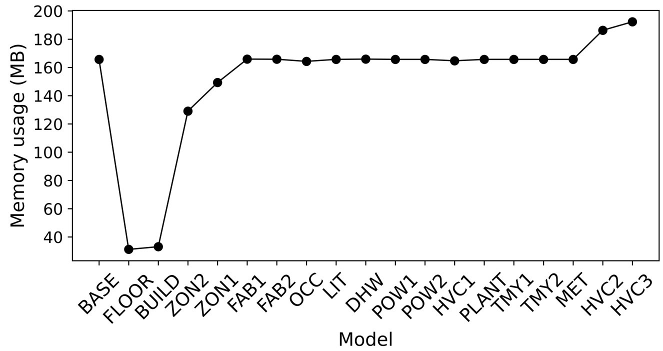

Figure 5: Resulting model memory usage: ZON1 and ZON2 show potential for memory usage reduction while preserving model accuracy.

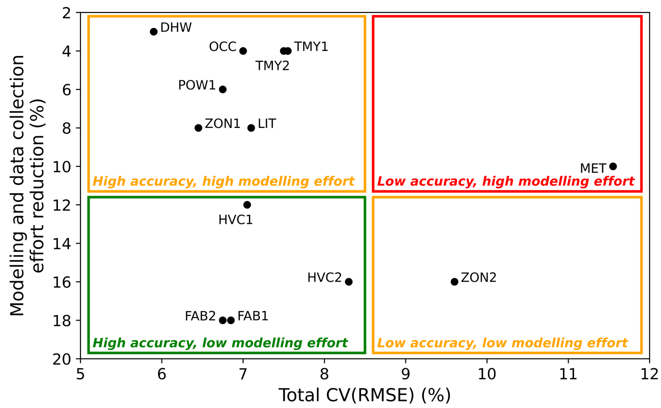

Figure 6: Summary matrix: CV(RMSE) versus estimated reduction in modelling and data collection effort.

Figure 6 summarises the trade-offs between accuracy and ease of data collection and modelling for shortlisted models. It confirms that U-value measurements and detailed site audits for zone HVAC equipment may be considered unnecessary for high accuracy and reduced effort (FAB1&2, HVC1&2). However, over-simplifying zone geometry (ZON2) can lower accuracy and should be done cautiously. Accurate meter data are crucial, and despite being time-consuming, pre-processing is recommended (MET).

Discussion

This study showed that accuracy is possible with limited data, but some requirements remain essential:

1. Collect plant HVAC technical specifications, and equipment power densities or occupancy information, depending on the building type.
2. Prioritise the use of AMY over TMY weather files.
3. Use zone-typing for geometry and avoid over-simplified layouts.
4. Ensure accuracy of the meter data.

The detail of these requirements may vary from one building to another. Simplification decisions should be carefully considered based on the building, climate, and modelling objectives (Cheng et al., 2024; Derakhti et al., 2022). Below are a few points which may need to be considered when working with limited data:

1. The building type and purpose.
2. Different zone types and activity patterns.
3. Alignment of simplification methods with BEM objectives (policy design, compliance, retrofit testing, ECM implementation).
4. Focus data collection and modelling efforts on parameters most influencing energy outputs and calibration.

CONCLUSIONS

BEM is a valuable tool for designing and implementing net zero built environment policies. Ensuring BEM accuracy is essential but often involves extensive data collection and modelling, especially challenging for older buildings with lower-quality or inaccessible data. This study shows with the help of a white-box model that some model simplifications have significantly lower accuracy penalties than others. While the baseline model required in-situ U-value measurements, extensive site audits, Wi-Fi monitoring, and comprehensive document reviews, simplified models achieved accurate calibration using more accessible data sources and simplified modelling methods. Based on a single case, this study acknowledges limited generalisability of findings due to building diversity. Simplifications' relevance may vary depending on building functions. However, the methodological framework presented here is designed for flexibility and can be adapted to analyse a diverse array of non-domestic buildings. Key learnings therefore include understanding the building's purpose and activity patterns and focusing efforts on the most sensitive input parameters. Additionally, simplifications should align with the BEM's purpose to maintain usefulness. Appropriate simplifications of a similar kind may also improve urban building energy modelling (UBEM) methods, reducing error aggregation at larger scales and supporting global UBEM policy-making efforts.

FUTURE WORK

Future work will include investigating the impact of ECMs on the shortlisted simplified models, considering the sensitivities of different input parameters on simulated energy consumption.

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