Assessing the impact of modelling variability on building performance simulation results

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Abstract

A modelling framework that applies a design-for-performance approach to predict the actual operational energy consumption of buildings was presented in the latest published CIBSE TM54 (2022) in the UK. However, modelling uncertainty can lead to discrepancies between predicted and actual energy consumption. Identifying these uncertainties is crucial for enhancing the reliability of building performance simulation approaches. This study developed a modelling task for practitioners based on a simplified school building . The requirement was to simulate energy use in IES VE or DesignBuilder software using either the template-level HVAC modelling or detailed component-level HVAC modelling approaches proposed in CIBSE TM54. The predicted annual natural gas and electricity consumption from the 20 participants showed substantial variability, ranging from -74.8% to 157.7% and -74.3% to 114.9%, respectively. This paper contributes to further improvement and detailing of modelling framework in the future.

Key Innovations

- Simultaneously examines the impact of variability in modelling approaches, modellers, and inter-model differences on the results.
- Discusses the trade-off between modelling reliability and the time required.

Practical Implications

The modeller's decision, the modelling software or the modelling approach can have a significant impact on the energy simulation results. The modelling framework and the workflow of the software application should be further refined to mitigate the introduction of unnecessary uncertainties.

Introduction

Energy modelling tools are widely developed and applied to predict building performance. To reduce the performance gap between predicted results and actual energy use, it is essential to explore the impact of modelling uncertainty on the results. The literature is reviewed below from three perspectives. First, in terms of modeller variability, previous studies have compared the results from different users simulating the same building using the same modelling software and approach, which revealed that the modeller's understanding of the building information and modelling decisions can have a non-negligible impact on the predicted outputs (Bloomfield, 1988; Gilles Guyon, 1997; Bradley, Kummert and McDowell, 2004; Berkeley, Haves and Kolderup, 2014). Next, in terms of inter-model variability, each type of software uses different algorithmic procedures and assumptions, which leads to different results when modelling the same project. Poor consistency of simulation results was found by having individual users modelling the same building using different modelling software (Underwood, 1997; Hopfe et al., 2007; Schwartz and Raslan, 2013; Reeves, Olbina and Issa, 2015; Choi, 2017; Magni et al., 2021). Finally, regarding the variability of modelling approaches, studies have mainly focused on discussing the differences between compliance and performance modelling, as well as comparing the results of quasi-steady state approaches and dynamic simulations (Murray, Rocher and O'Sullivan, 2012; Jones, Fuertes and de Wilde, 2015; Jradi et al., 2018; Shiel, Tarantino and Fischer, 2018; Jradi, 2020). Few studies have explored the reliability comparison between template HVAC modelling and detailed component-level HVAC modelling. A study that categorised energy use intensity (EUI) into HVAC-related and non-HVAC-related found that the maximum gap between predicted energy consumption and measured data for HVAC systems was 114.7%, while the maximum performance gap for non-HVAC systems was only -4.5% (Wang et al., 2020). Therefore, modelling of HVAC systems and controls needs to be given more attention.

Overall, the complexity of HVAC system inputs has led previous studies to mainly select simplified HVAC modelling as the research approach. This ignores the trade-off between complexity and reliability of different dynamic performance modelling. The aim of this study is to investigate the effect of modeller variability, inter-model variability and modelling approach variability on the results by analysing the actual modelling results. Different users were asked to model the same building in IES VE or DesignBuilder software using either template HVAC modelling or detailed component-level HVAC modelling approaches to explore the impact of uncertainty in modelling on energy predictions by comparisons of inputs and outputs.

Methods

In this study, a 2970 m^2 real sixth form school building located in England was simplified to develop this modelling task. Figure 1 illustrates the building model developed in IES VE software. The model has 31 zones,

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and the main activity types are teaching, workshops and offices. Table 2 presents an overview of the building's HVAC system, providing an initial insight into the composition of end-use energy consumption. In brief, gas-fired condensing boilers are used for the main space heating. The ICT-enhanced classrooms and IT rooms are supplied with the variable refrigerant flow (VRF) system for heating and cooling. Two server rooms are equipped with the direct expansion (DX) system for cooling. The automatic vents in three atrium spaces provide natural ventilation by responding to the temperature and CO_2 concentrations. The other spaces are mechanically ventilated through an air handling unit (AHU) with heat recovery and there is no dedicated cooling system. Domestic hot water (DHW) is heated by a separate gas water heater.

Figure 1: Building model developed in IES VE.

Table 1: an overview of the building's HVAC system.

Categories	Details
Heating	• Three gas-fired condensing boilers are used for the space heating. • The ICT-enhanced classrooms and Business & IT rooms are equipped with the VRF system for heating.
Cooling	• The ICT-enhanced classrooms and Business & IT rooms are equipped with VRF systems for cooling. • The two server rooms are each equipped with DX units for cooling.
Domestic hot water	• A separate gas-fired water heater to produce hot water.
Ventilation	• The first row of glazing at the top of the curtain walls in the three atrium spaces can be opened automatically to provide natural ventilation. • The rooms excluding the three atrium spaces are mechanically ventilated by a central AHU with heat recovery.

Participants were asked to choose one of the two modelling approaches (template level and detailed component-level) proposed by CIBSE TM54 (2022), using either IES VE or DesignBuilder software, which are the most widely used building performance modelling platforms in the UK, to predict the building's operational energy consumption. The UK CIBSE TM54 (2022) protocol was developed to facilitate the application of performance modelling to predict operational energy consumption at the design stage, which can avoid the misuse of compliance models as design tools or benchmarks to quantify performance gaps. Two levels of dynamic modelling approaches are available for this modelling framework: (1) Template-level modelling is the application of a predefined template HVAC system with input of key parameters, corresponding to the Apache system in IES VE software and the Simple HVAC method in DesignBuilder software; (2) Detailed component-level modelling refers to the creation of project-specific HVAC schematics based on each component, which corresponds to the Apache HVAC system in IES VE software and the Detailed HVAC method in DesignBuilder software.

Participants were recruited through several channels, such as DesignBuilder monthly newsletter for UK subscribers, the CIBSE Building Simulation Group and UCL alumni network. Participants were required to have a solid understanding of UK building regulations and standards, along with relevant work experience in modelling. Therefore, 20 practitioners with at least 1 year of experience in building performance modelling were recruited and all had an educational background or work experience in the UK. Each modelling approach was tasked by 5 participants under each software. All participants were provided with the same modelling package, which included an overview of the modelling task (which detailed envelope thermal performance, building services system characteristics, and occupant information), a gbXML file for this building, a weather file, and technical information sheets for key HVAC system equipment. Additionally, a questionnaire was developed based on this modelling task to obtain feedback from the practitioners' perspectives for a qualitative analysis of the existing modelling challenges and drivers of variation in the results. Also, it can be used to collect basic information about the participants and the time spent on their modelling. All participants completed the modelling task and submitted their final models and questionnaires. This paper only shows a quantitative analysis of the simulation results, a detailed comparison of the modelling parameters and results as well as a qualitative analysis based on the questionnaires will be part of future work.

Results

This part first describes the composition of the participants. The simulation results for natural gas and electricity use are then compared to the average of the results. Furthermore, differences in energy consumption projections for each end-use are investigated. Finally, the time required by participants to apply the different modelling approaches is examined.

Background and experience of participants

20 practitioners completed the modelling task and the associated questionnaire. Figure 2 shows the professional composition of the participants. There were 7 building physicists, 7 sustainability consultants, 2 researchers and 4 individuals who specifically identified their roles as building performance modellers. The questionnaire included options for architects and building services engineers and interestingly, no participants identified themselves in these professional roles, which may

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indicate that building performance modelling is often outsourced rather than done by the original designer. Regarding the years of work experience, as shown in Figure 3, only one participant had more than 10 years of work experience. 12 participants had 4-10 years of work experience, while the other 7 were in the early stages of their careers (1-3 years).

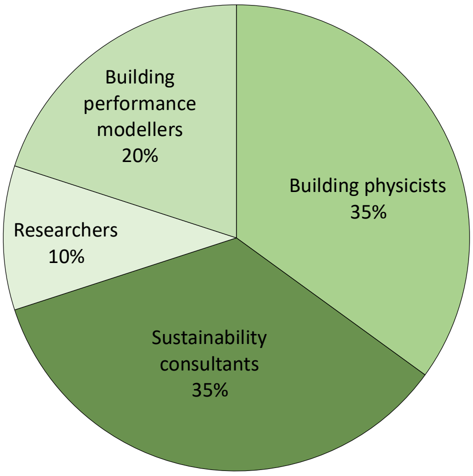

Figure 2: Professional role.

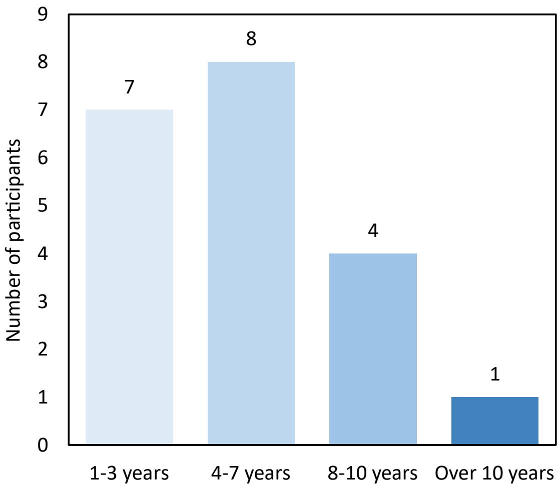

Figure 3: Years of work experience.

Fuel type breakdown of prediction deviations

Tables 2 to 4 respectively present the comparison of each participant's predicted natural gas, electricity, and total energy consumption with the average for the entire sample.

The mean simulated natural gas energy consumption was 105.6 MWh (35.6 kWh/m^2). The benchmarks for natural gas EUI in secondary schools in the UK are 86 kWh/m² for 'good practice' and 113 kWh/m² for 'typical practice' (CIBSE, 2021). This suggested that simulated natural gas usage for this building was energy efficient, even lower than the ‘good practice’ benchmark. By software type, the average simulation result for the 10 participants using DesignBuilder software was 63.4 MWh, compared to 147.8 MWh for those using IES VE software. By modelling approach, the average simulation result for template HVAC modelling was 107.9 MWh, whereas detailed component-level HVAC modelling yielded an average of 103.4 MWh.

Table 2: Comparison of individual predictions with the average for natural gas consumption.

Approach	User	Results (MWh)	Variation	Variation range
DB: Simplified	1	28.6	-72.9%	-72.9% ~ -15.3%
	2	89.5	-15.3%	
	3	85.0	-19.6%	
	4	29.5	-72.1%	
	5	65.5	-38.0%	
DB: Detailed	6	26.6	-74.8%	-74.8% ~ 7.8%
	7	75.2	-28.8%	
	8	113.9	7.8%	
	9	76.9	-27.1%	
	10	43.0	-59.3%	
IES: Simplified	11	87.4	-17.2%	-33.2% ~ 157.7%
	12	126.2	19.5%	
	13	224.3	112.4%	
	14	272.1	157.7%	
	15	70.5	-33.2%	
IES: Detailed	16	103.1	-2.3%	-5.6% ~ 137.3%
	17	250.6	137.3%	
	18	138.6	31.2%	
	19	99.7	-5.6%	
	20	105.8	0.2%	

The mean simulated electricity consumption was 168.2 MWh (56.6 kWh/m^2). The benchmarks for electricity EUI in secondary schools in the UK are 42 kWh/m² for 'good practice' and 51 kWh/m² for 'typical practice' (CIBSE, 2021). This demonstrated that the building's projected electricity use was higher than the ‘typical practice’ benchmark. When comparing software types, the average electricity consumption for DesignBuilder simulation was 167.4 MWh, while IES VE simulations averaged 169.1 MWh. In terms of modelling approaches, the average electricity consumption for template HVAC modelling was 130.2 MWh, whereas detailed component-level HVAC modelling resulted in an average of 206.3 MWh.

Table 3: Comparison of individual predictions with the average for electricity consumption.

Software: Approach	User	Results (MWh)	Variation	Variation range
DB: Simplified	1	43.3	-74.3%	-74.3% ~ -10.1%
	2	73.4	-56.4%	
	3	151.3	-10.1%	
	4	122.7	-27.1%	
	5	147.8	-12.1%	
DB: Detailed	6	136.8	-18.7%	-18.7% ~ 114.9%
	7	163.6	-2.7%	
	8	361.6	114.9%	
	9	311.6	85.3%	
	10	162.0	-3.7%	
IES: Simplified	11	148.5	-11.7%	-58.7% ~ 67.1%
	12	147.5	-12.3%	
	13	69.4	-58.7%	
	14	281.1	67.1%	
	15	116.9	-30.5%	

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IES: Detailed	16	148.2	-11.9%	-24.2% ~ 38.1%
	17	229.3	36.3%	
	18	127.5	-24.2%	
	19	190.2	13.0%	
	20	232.2	38.1%	

For total energy consumption, which is the sum of natural gas and electricity consumption, the simulation results show an average of 273.8 MWh. The DesignBuilder software simulation has an average total energy consumption of 230.8 MWh, while the IES VE software has a higher average of 316.9 MWh. Regarding modelling approaches, template HVAC modelling resulted in an average total energy consumption of 238.0 MWh, while detailed component-level HVAC modelling averaged 309.7 MWh.

Table 4: Comparison of individual predictions with the average for total energy consumption.

Software: Approach	User	Results (MWh)	Variation	Variation range
DB: Simplified	1	71.9	-73.7%	-73.7% ~ -13.7%
	2	162.8	-40.5%	
	3	236.2	-13.7%	
	4	152.2	-44.4%	
	5	213.3	-22.1%	
DB: Detailed	6	163.4	-40.3%	-40.3% ~ 73.6%
	7	238.8	-12.8%	
	8	475.5	73.6%	
	9	388.6	41.9%	
	10	205.0	-25.1%	
IES: Simplified	11	236.0	-13.8%	-31.6% ~ 102.0%
	12	273.6	-0.1%	
	13	293.8	7.3%	
	14	553.2	102.0%	
	15	187.4	-31.6%	
IES: Detailed	16	251.3	-8.2%	-8.2% ~ 75.3%
	17	480.0	75.3%	
	18	266.0	-2.9%	
	19	289.9	5.9%	
	20	338.0	23.4%	

End-use breakdown of prediction deviations

Natural gas was consumed for space heating and domestic hot water (DHW), and individual results and comparisons against average projections for each end use shown in figures 4 and 5, respectively. The red dotted lines and numbers in the figures represent the average of all the simulated results. To enable effective comparison, the y-axis range in the following two figures is set to the same scale, allowing for a clear visualization of the proportion of these two end-uses in the total natural gas consumption. Notably, all figures show the results in the same order as the participants listed in the previous three tables.

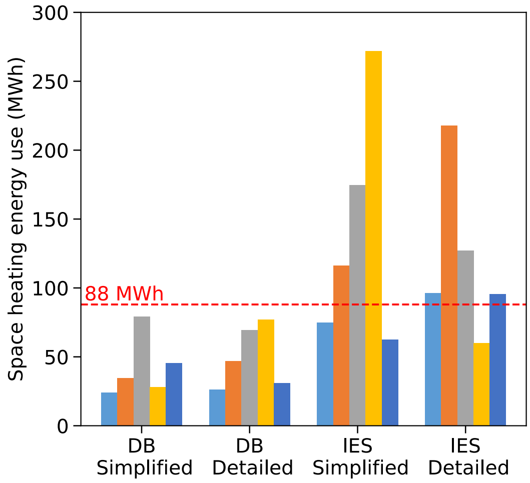

Figure 4: Predicted space heating energy use: Individual variations and mean value.

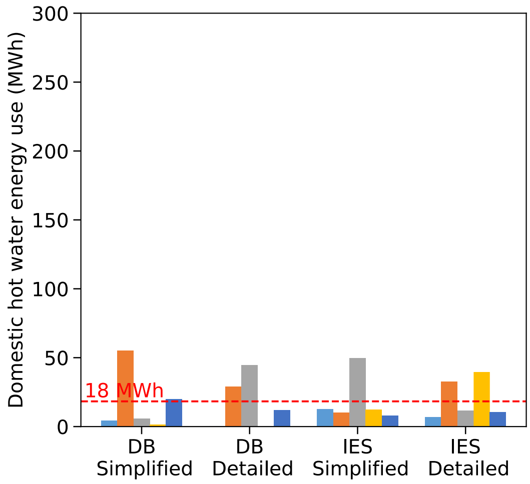

Figure 5: Predicted domestic hot water energy use: Individual variations and mean value.

The simulated mean value of natural gas consumption for space heating was 88.0 MWh, with a standard deviation of 64.8 MWh. The results for the 10 participants using the DesignBuilder software were all below this mean, with an average of 46.2 MWh. In contrast, the simulated mean for the IES VE users was 129.7 MWh, with only three participants simulating results below the overall average. For DHW, the average of all modelling results was 18.3 MWh with a standard deviation of 16.8 MWh, in which one participant did not have a DHW system set up. The investigation of the groups, based on different modelling software and approaches, revealed that the mean values of each group were within ±1.2 MWh of the overall mean.

Electricity consumption included space heating and cooling provided by the VRF system and the DX system, auxiliary energy use, lighting and equipment operation. Figures 6 to 9 illustrate individual variations in simulation results for each category. Similarly, the y-axis range in these four figures is also standardized.

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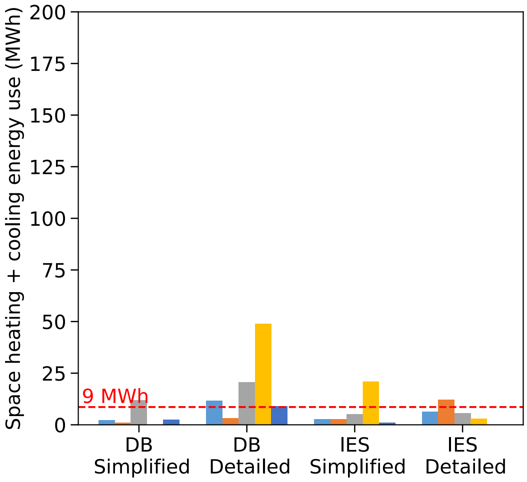

Figure 6: Predicted Space heating + cooling energy use: Individual variations and mean value.

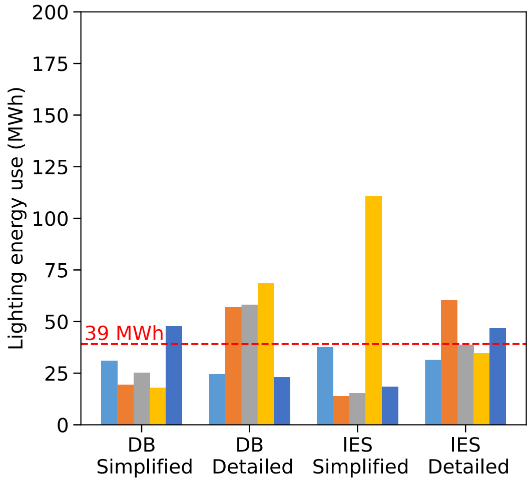

Figure 8: Predicted lighting energy use: Individual variations and mean value.

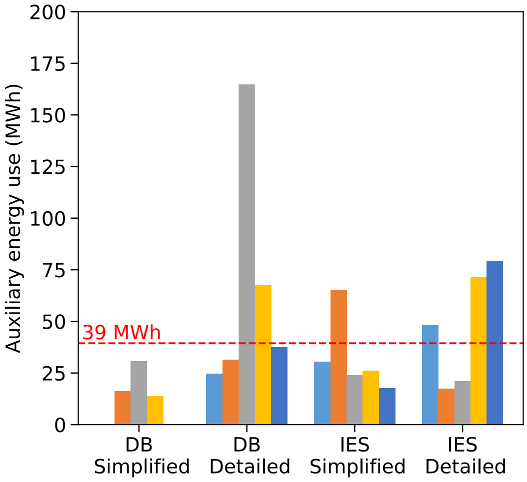

Figure 7: Predicted auxiliary energy use: Individual variations and mean value.

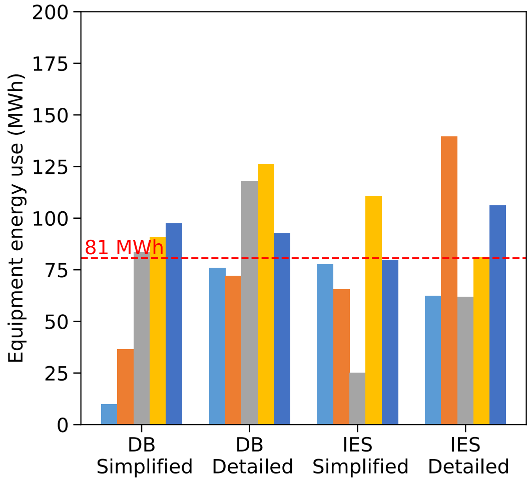

Figure 9: Predicted equipment energy use: Individual variations and mean value.

For electricity use for space heating and cooling, the mean value of the simulation output for the 20 participants was 8.6 MWh, with a standard deviation of 11.1 MWh. Generally, the mean value of the simulation results from the DesignBuilder software (11.2 MWh) was higher than that from the IES VE software (6.0 MWh). By modelling approach, the mean value of simulation results using the detailed component-level HVAC modelling approach (12.1 MWh) was higher than that using the template HVAC modelling approach (5.1 MWh). The predicted consumption of auxiliary energy had an average value of 39.4 MWh and a standard deviation of 36.3 MWh. The mean results from different modelling approaches showed a significant difference, with the predicted mean under the template HVAC modelling being 22.4 MWh and the detailed component-level HVAC modelling being 56.3 MWh.

The simulated electricity usage for lighting resulted in a mean value of 39.1 MWh with a standard deviation of 22.9 MWh. For equipment, the simulated results had a mean value of 80.6 MWh, with a standard deviation of 31.7 MWh. Both types of end-use energy predictions showed similar average values across the different modelling software. However, when classified according to the different modelling approaches, the simulation results averages for the template HVAC modelling (33.8 MWh for lights and 67.7 MWh for equipment) were both lower than the detailed component level HVAC modelling (44.4 MWh for lights and 93.6 MWh for equipment).

Variation in modelling time among participants

In the questionnaire participants were asked to self-report the time spent on the modelling task. The question was set with five options including less than two hours, 2-5 hours, 5-10 hours, 10-15 hours and more than 15 hours. Figure 10 illustrates the proportion of time spent on the modelling task. Almost half of the participants (9) spent 5-10 hours modelling. Six participants used 2-5 hours to complete the task. Two used 10-15 hours to model. The

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other three modellers reported more than 15 hours. No one was able to complete the energy modelling of the building in less than two hours.

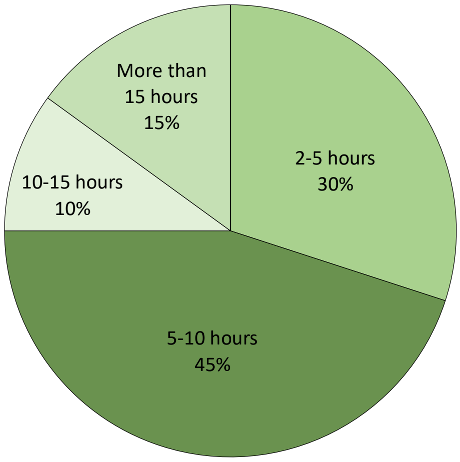

Figure 10: Proportion of time spent on the task

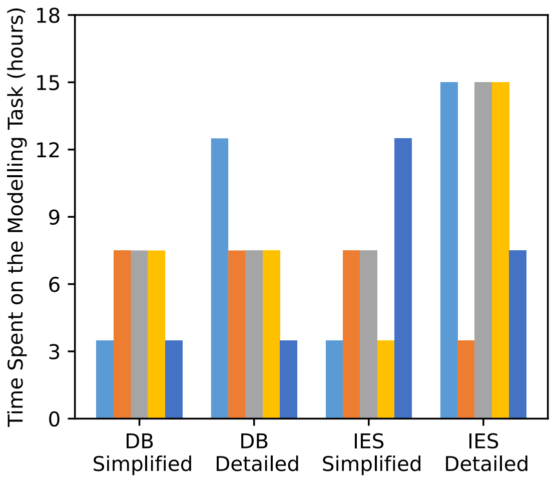

Figure 11: Self-reported time required for the task

Figure 11 displays the distribution of time taken by each participant to complete the modelling task, categorised by modelling software and approach. The median value was used as a proxy for the time range. Hence, the five options are replaced with 2 hours, 3.5 hours, 7.5 hours, 12.5 hours and 15 hours in the figure. It was observed that modellers who reported spending more than 15 hours on modelling used the same modelling approach and software, which was the Apache HVAC system in the IES VE software. The average modelling time for this group of participants amounted to 11.2 hours. In comparison, the average time required to complete the task using the template HVAC modelling approach in the IES VE software was only 6.9 hours. For the DesignBuilder software, the five participants using the template HVAC modelling approach took an average of 5.9 hours and 7.7 hours for detailed component-level HVAC modelling.

Discussion

The predicted annual energy consumption for natural gas by the 20 participants varied from -74.8% to 157.7% of the average, while the electricity predictions ranged from -74.3% to 114.9%. For total energy consumption, the range of differences narrows slightly to -73.7% to 102.0%. This smaller variation compared to natural gas and electricity individually is due to the cancelling out effects of the simulation results for each fuel type. Thus, it is necessary to investigate the consumed energy for each end-use, which prevents misinterpretation of the simulation due to mutual cancellation.

Comparing the simulation outputs of the different software, it was found that the average value of natural gas usage simulated by the IES VE software was 2.3 times higher than that of DesignBuilder. The average value of electricity use simulated by both software is almost the same. The simulation results for total energy consumption were 1.4 times higher for IES VE than for DesignBuilder. The simulated averages for natural gas consumption were shown to be nearly identical when compared according to the modelling approach. However, the detailed component level HVAC modelling approach predicted about 58.5 % higher mean values for electricity consumption than the simple HVAC modelling approach, and about 30.1 % higher predictions for total energy consumption. In summary, for natural gas consumption, the simulations using the DesignBuilder software resulted in lower predictions. For electricity consumption, the simulations performed under the simplified HVAC modelling approach had lower energy use.

To further understand the factors determining the simulation results for natural gas and electricity, the energy use of each end-use was then compared. It was found that the simulated energy consumption for each type of end-use had high variability. By comparing the standard deviation of each group, results for natural gas required for space heating were predicted to have the most dispersion. Relatively less variability was demonstrated in the simulated results for natural gas required for DHW and for space heating and cooling using electricity.

In detail, for natural gas consumed for space heating, the energy projections varied from the average value by a range of -72.4% to 209.4%. The average value of the IES VE software simulation results was 2.8 times higher than DesignBuilder. However, for domestic hot water, the mean value for each group did not fluctuate by more than 6% from the mean value of the total simulation results, whether categorised according to different software or modelling approaches. This demonstrated that space heating accounted for the largest share of natural gas consumption, indicating that it was the main driver of natural gas demand in the modelling.

For electricity use predictions, the average of simulation results for each end-use under the detailed component-level HVAC modelling approach was higher than for the template HVAC modelling. One potential reason for this was that the detailed component-level HVAC modelling approach had more comprehensive and advanced data input requirements when modelling HVAC systems and auxiliary energy. However, for the simulation of lighting and equipment operation, the data inputs for the two modelling approaches are essentially identical, and they

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depend on the activity type template assigned to each space. Therefore, further investigation of modelling input parameters is required in the future for understanding the underlying causes of the discrepancies in modelling.

This study did not set a time limit for completing the task. The average time taken by the 20 practitioners to complete the modelling was 7.9 hours. Under the same modelling approach, the average time required by participants using DesignBuilder was lower overall than that of IES VE users. With the same modelling software, the average time to complete detailed component level HVAC modelling was longer. However, the time required for modelling did not correspond to the magnitude of result variations. For example, for the simulation of total energy consumption, the largest range of variation in results was among the five participants who used the template HVAC modelling approach in the IES VE software (-31.6% ~ 102.0%), while the minimum range of variation was among those who used the template HVAC modelling approach in the DesignBuilder software (-73.7% ~ -13.7%). This demonstrated that increased modelling detail requires more time and effort from the modeller, while at the same time the increase in input parameters may introduce additional uncertainty leading to greater variation in results.

Conclusion

This paper presented the first part of a study, focusing solely on the analysis and discussion of simulation results provided by the participants. The results indicated that the modeller's decision, the modelling software or the modelling approach can have a significant impact on the energy simulation results. The distance and lack of communication between building designers, modellers and software developers may be a major reason for the various discrepancies. Thus, the modelling framework and the workflow of the software application should be further refined to mitigate the introduction of unnecessary uncertainties. For example, adding the process of reviewing the models by the original designers and benchmarking based on measured performance of similar projects in the past. Moreover, to explore the optimisation of data-driven modelling and machine learning algorithms for complex building design and energy prediction (Manfren, James and Tronchin, 2022; Golafshani *et al.*, 2024). The next step in this work will be to investigate the modeller's key input parameters, especially for the HVAC system, and to conduct a qualitative analysis based on the questionnaire to further identify the reasons for the introduction of uncertainty.

As with other similar studies, a limitation of this study is the lack of comparison with actual energy consumption data (Gilles Guyon, 1997; Berkeley, Haves and Kolderup, 2014). To make the time required for the modelling task manageable for practitioners, and considering the difficulty of recruitment and budget constraints, this study simplified the modelling of a real school building and participants were asked to apply a typical occupancy pattern for simulation that was in accordance with the National Calculation Methodology (NCM) in England. Not only did this result in an inability to use actual energy consumption data from the original building for comparison, it also ignored the impact of occupancy uncertainty on the modelling results. In practice occupancy variability makes the model less reliable. Therefore, comparing modelling results with measured performance can help to identify extra-curricular activities and other non-standard occupancy patterns to optimise modelling inputs. In the future, the same simplification can be applied to the calibrated original model and simulated to represent the best practice model.

Furthermore, this study focused on the uncertainty in the input of modelling information. As a result, gbXML files, one of the most common building information transfer formats, were only used to ensure the consistency of building geometries, and their potential and reliability for other information transfers were not investigated in depth. Future work could explore the uncertainties that different users or software might introduce when applying BIM-based modelling, in line with the six components (1. Geometry; 2. Constructions and materials; 3. Spaces type; 4. Thermal zones; 5. Space loads; 6. HVAC system and components) proposed by Maile, Fischer and Bazjanac (2007) for the ideal transfer of information between BIM and BEM.

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