A case study of the approaches used and accuracy of performance modelling for non-domestic buildings in the UK.

Abstract

The UK's goal of transitioning to net zero carbon buildings has led to an increasing focus on the reliability of modelling results for energy consumption. Detailed modelling of HVAC systems and controls is considered a breakthrough in improving model accuracy. This paper uses a school building as a case study. Two dynamic simulation approaches, template and detailed component level HVAC modelling, are used in the IES VE software to predict energy consumption and compare the results with measured data. The root causes of the performance gap are analysed based on the calibration of the models. At the same time, this study trades off the complexity of the performance modelling input parameters against the accuracy of the output results. Then explore the interoperability of input parameters in these two approaches to avoid additional uncertainties introduced by detailed modelling. Some insights are provided into the modelling of operational energy use for non-domestic buildings in the UK.

Background

In the context of the current energy price crisis and climate emergency, there is an urgent need for the UK building industry to make the transition to Nearly Zero-Energy Buildings (NZEB) by adopting cost-effective ways to improve energy efficiency. The UK government has recast the Approved Document Part L in 2021, requiring a further 30% reduction in CO_2 emissions for new dwellings and 27% for non-domestic buildings. However, there is a mismatch between design expectations and actual energy consumption due to the existence of the energy performance gap (Carbon Trust, 2011). Incorrect use of regulation-oriented compliance models is likely to send the wrong signal that the building's energy consumption is meeting set targets. Therefore, it is essential to accurately predict the building's operational energy performance during the design stage. On the other hand, identifying the root causes of the performance gap also facilitates the selection of optimal improvement measures during the in-use stage. Overall, the prerequisite for achieving net zero is to bridge this gap rather than simply limiting carbon emissions through regulation (LETI, 2020). Nevertheless, both the Standard Assessment Procedure (SAP) used for predicting energy consumption in residential buildings and the National Calculation Method (NCM) used for non-residential buildings base their calculations on a set of assumptions under standard conditions, whilst they ignore unregulated energy use. Hence, there is a need to seek alternatives to compliance modelling for predicting building operational performance and quantifying the gap.

In light of the above, CIBSE TM54 (2022) provides a practical framework to evaluate operational energy consumption, which classifies dynamic simulation into template HVAC modelling and detailed component level HVAC modelling. The template level means that the users select predefined template HVAC systems and customize key parameters in these systems (ibid.). The detailed component level refers to tailoring a specific HVAC system based on the performance of each component in the project (ibid.). Currently, there is no mandatory requirement for the level of modelling detail in the UK. Besides, The Design for Performance (DfP) initiative is launched in the UK now to reduce the performance gap and improve energy efficiency by adapting the Australian NABERS commitment agreement protocol to the UK context (Bannister, Cohen and Bordass, 2016). Analysis of the DfP pilot projects showed that even when the performance modelling in accordance with the NCM was followed, the error in the predicted results due to the lack of a detailed HVAC system analysis was still difficult to eliminate (Cohen, Ratcliffe and Bannister, 2018). On the contrary, Ahmad and Culp (2006) found that complex input parameters introduced additional uncertainty leading to larger discrepancies. However, it is worth noting that the model they developed was not calibrated.

The development of building performance modelling requires the application of advanced simulation software. Each type of software adopts different algorithms programs and assumptions, which lead to discrepancies in produce results (Strachan et al., 2016; Choi, 2017; Elnabawi, 2020). Besides, the design space of the input parameters is affected by the modeller's comprehension and decision-making of building information. This human-introduced uncertainty can affect the accuracy of the output as well (Gilles Guyon, 1997; Bradley, Kummert and McDowell, 2004; Berkeley, Haves and Kolderup, 2014). Overall, unrealistic modelling and simulation assumptions contribute to the performance gap. In particular, the complexity of the HVAC system inputs has led existing studies to either simplify these input values or to avoid in-depth analysis. In this paper, a school building is modelled separately at the template HVAC level and at the detailed component HVAC level using IES VE software and the results are compared with measured data. Figure 1 shows the parameter setting interface of the two modelling methods in the IES VE software. Simultaneously, an attempt is made to provide some insight into the cut-off points for model accuracy and complexity.

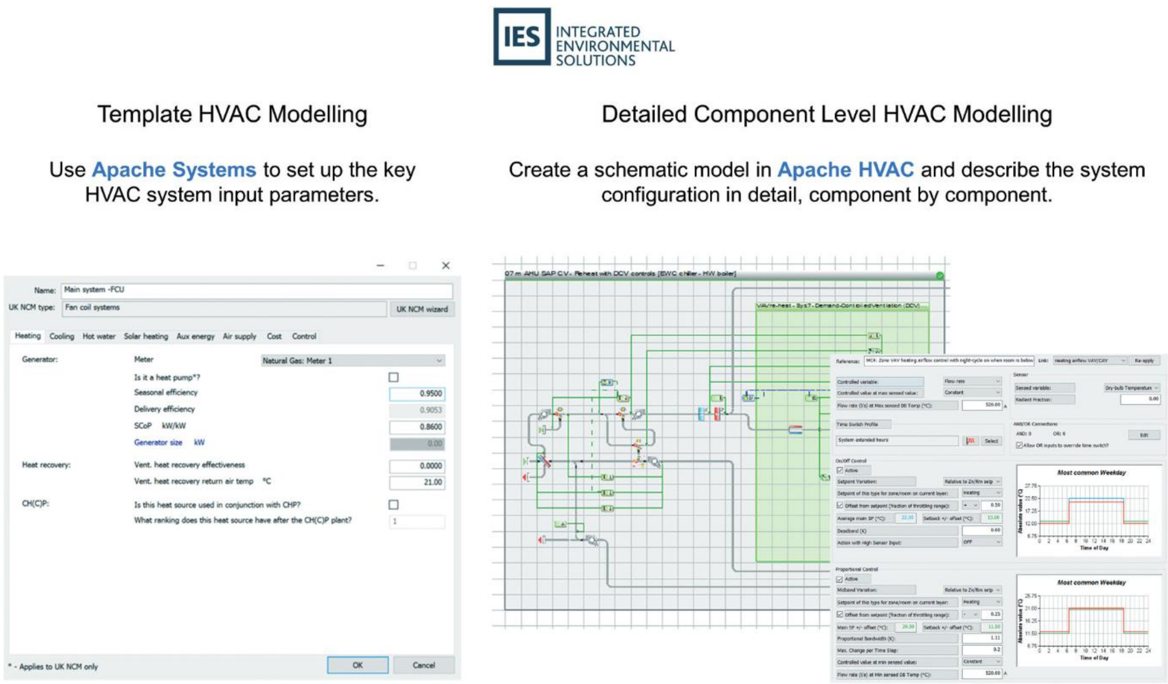

Figure 1. Illustration of ‘template’ and ‘detailed’ HVAC system modelling in IES software (CIBSE, 2022)

Methodology

The modelling framework applied in this paper is based on CIBSE TM54 (2022) to assess the impact of the level of detail in modelling HVAC systems on energy prediction. As a widely used software by practitioners, IES VE was adopted for this study. An existing school building was modelled using the Apache module and the Apache HVAC module of this software respectively. The occupancy and all end uses of the building were established in a previous post-occupancy evaluation study (Burman, 2016). Thus, the input data was derived from real operational data collected on-site, such as temperature set points, operational schedules, building equipment and occupant behaviour. The selected inputs following the UK NCM were fine-tuned manually on the basis of evidence and reasonable assumptions reflecting the building operation. The results of the iterations were compared with the measured values to validate that the model could meet the monthly calibration criteria specified in ASHRAE Guideline 14 (NMBE<±5%, CVRMSE<15%). Finally, the similarities and differences between the parameters of the two models were analysed. The feasibility of interconverting the input parameters and their potential to reduce modelling difficulties were also explored.

Case study

Figure 2. Building model developed for the case study with IES VE

The case study is a ~2970 m^2 Sixth Form building located in North-West England. This three-storey steel frame building was completed in summer 2010 and the main activity types are teaching, workshops and offices. The building model developed for this case study with IES VE is presented in Figure 2.

For the building structure and fabrics, the concrete and brick external walls are cavity structures and heavyweight construction materials are used to regulate temperature fluctuations. External shading is achieved by canopy structures and louvres. For the building services system, three gas-fired condensing boilers are used for the main space heating. This means that the hot water produced by the boilers flows mainly to the ceiling-mounted radiant panels and the heating coils in the air handling unit (AHU). The ICT-enhanced classrooms and IT workspaces are supplied with variable refrigerant flow systems for heating and cooling. The other spaces are cooled by ventilation only and no dedicated cooling system was designed. The automatic vents in the atrium space provide natural ventilation by responding to the temperature and CO_2 concentrations. The kitchen and toilets are fitted with local extract fans. Although there are manually operable vents, The remaining areas are mainly mechanically ventilated by AHU equipped with thermal wheels to recover heating energy. The domestic hot water was designed to be preheated by flat-plate solar thermal panels and has a separate gas-condensing storage water heater for supplementary heating. In reality, all boilers work in non-condensing mode and the solar system does not operate due to commissioning issues. The internal lighting is designed to be more efficient than 2 W/m²/100 lux, with sensors installed in the classrooms and corridors to control switching. For the measurement data, the utility supplier provided the gas and electricity consumption of the building for the full year. Based on the above information, the model can be developed in the IES VE and Table 1 shows the main input parameters.

Table 1. Input parameters for the building model

Categories	Details
External envelope	U-value (W/m^{2}K): External wall: 0.2; External floor: 0.21; Roof: 0.16; Window: 2.03; Door: 1.97. Air tightness: 9.09 m³/(m².hr) @ 50 Pa.
Occupancy	Nominal capacity: 250.

	Weekdays: 6:15-16:00 and extended to 18:00-21:00 on Tuesdays and Thursdays for night school. Weekends: unoccupied.
Heating	Gas-fired boilers operating in non-condensing mode. Seasonal efficiency: (1) Boilers: 86% (2) VRF system seasonal COP: 3.69 Weekdays 4:00-6:00 for preheating and 7:00-16:00 and extended to 18:00-21:00 on Tuesdays and Thursdays for night school.
Cooling	Energy Efficiency Ratio for the VRF system: 3.29. Same as the occupancy schedule.
Domestic hot water (DHW)	DHW delivery efficiency: 95%. Storage volume: 900 litres. Storage losses: 0.005 kWh/(l/day).
Ventilation	Specific Fan Power for AHU: 2.85 W/(l/s). Seasonal efficiency for the thermal wheel: 78%. Same as the occupancy schedule.
Lighting	Installed power density: 2 W/m^2/(100lux).

Results

1. Building energy performance

The simulation results of energy consumption by IES Apache module (template level analysis) and IES Apache HVAC module (detail component level analysis) are shown in Figure 3. The gap between simulation and actual data was less than ±2%, which indicated that both modules can reliably predict annual energy usage by fine-tuning the input parameters. To further verify the accuracy of these two modelling approaches, the simulated electricity and natural gas consumption were compared with the measured data using different time series spans respectively.

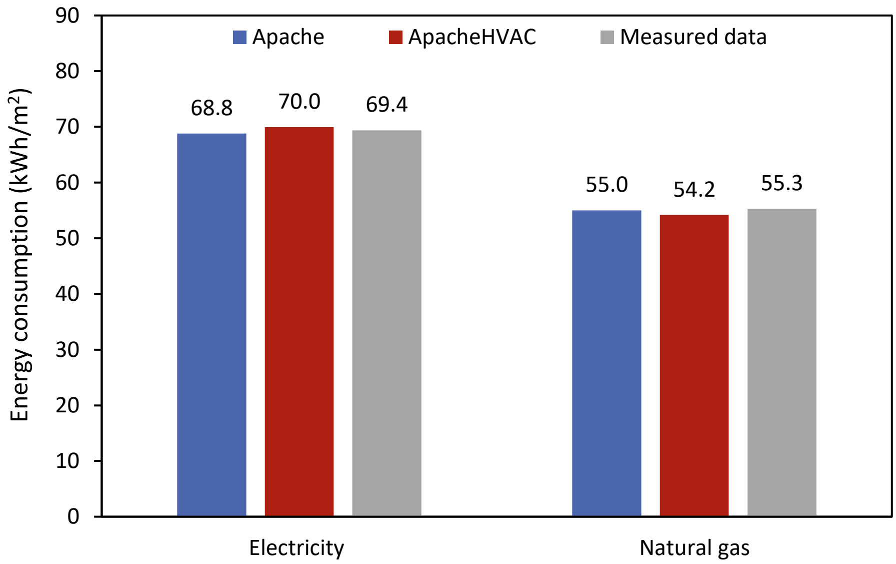

Figure 3. Simulated and measured annual energy consumption.

1.1 Electricity consumption

Figure 4 compares the monthly electricity usage. The average daily electricity usage for each week is presented in Figure 5. The outputs of both simulation modules were in general agreement and both NMBEs met the monthly calibration criteria, but the CVRMSEs were outside the acceptable limits. This implied that the monthly simulation errors cancel each other out resulting in a smaller systematic bias (NMBEs <±5%). In detail, the simulation results were lower than the measured values during the winter and holiday periods, while at other times the electricity consumption was overestimated. Furthermore, an unusual situation was that the lowest peak in actual electricity consumption occurred in the 23rd week (June), which was not the school closure period. Therefore, it is difficult to take these special circumstances into account in the modelling without conducting site visits.

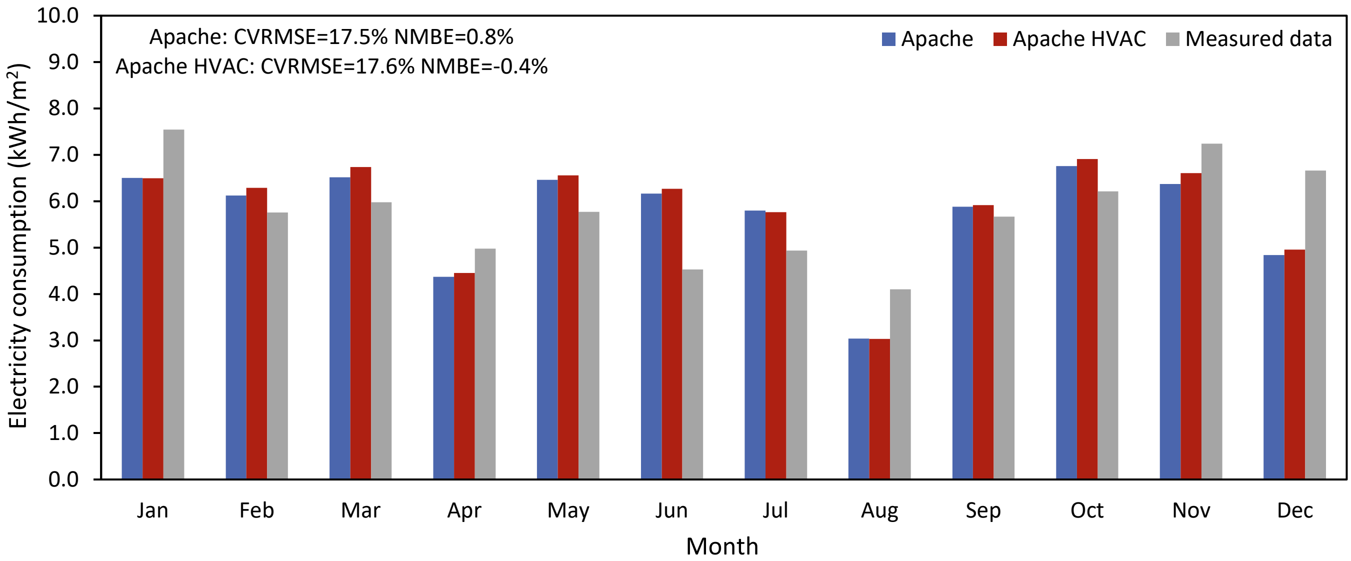

Figure 4. Simulated and actual monthly electricity usage

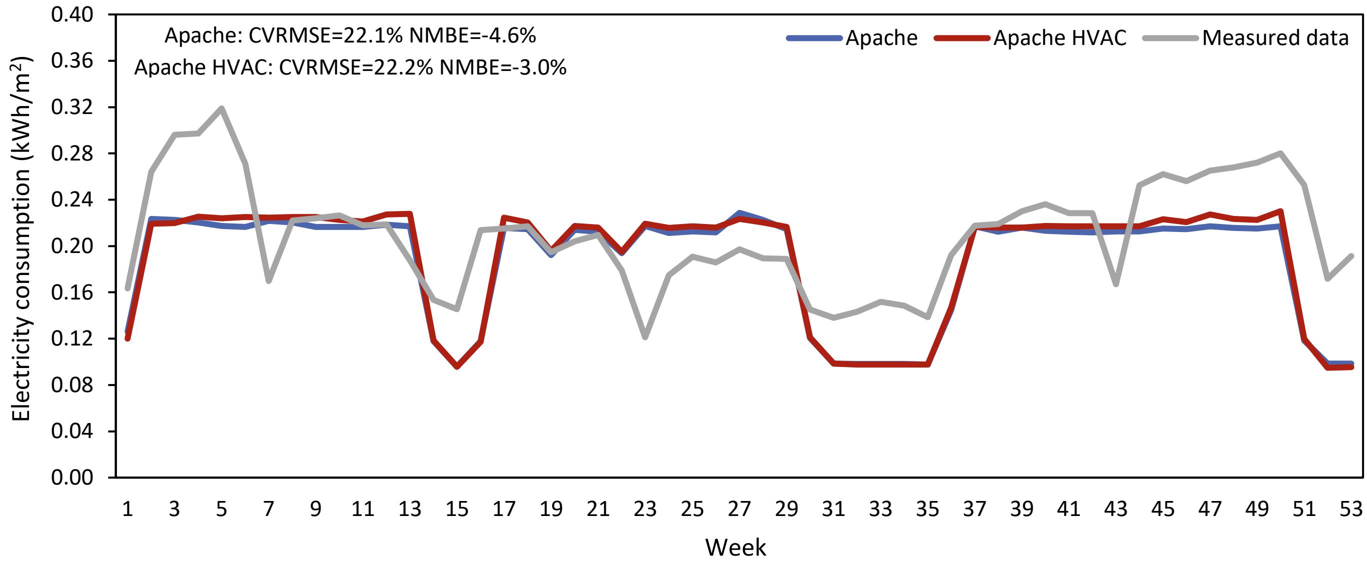

Figure 5. Average daily electricity consumption for each week

Figures 6 and 7 compare the simulated and actual electricity consumption for typical weekdays and weekends in the winter and summer respectively. The simulation results were closer to the measured data on weekdays in winter and weekends in summer. Building baseloads were consistently underestimated, which was likely to be the main reason for the poor simulation results for winter and holiday periods. In addition, electricity usage predictions for night school operating hours were not accurate.

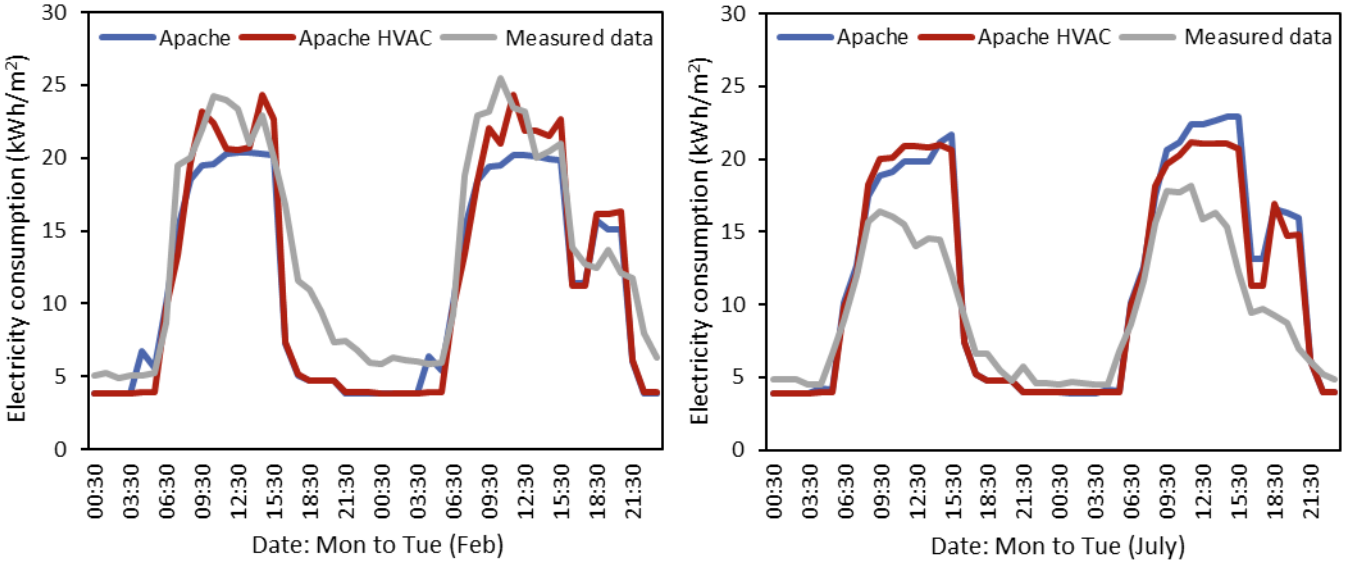

Figure 6. Hourly electrical demand during typical weekdays in winter and summer

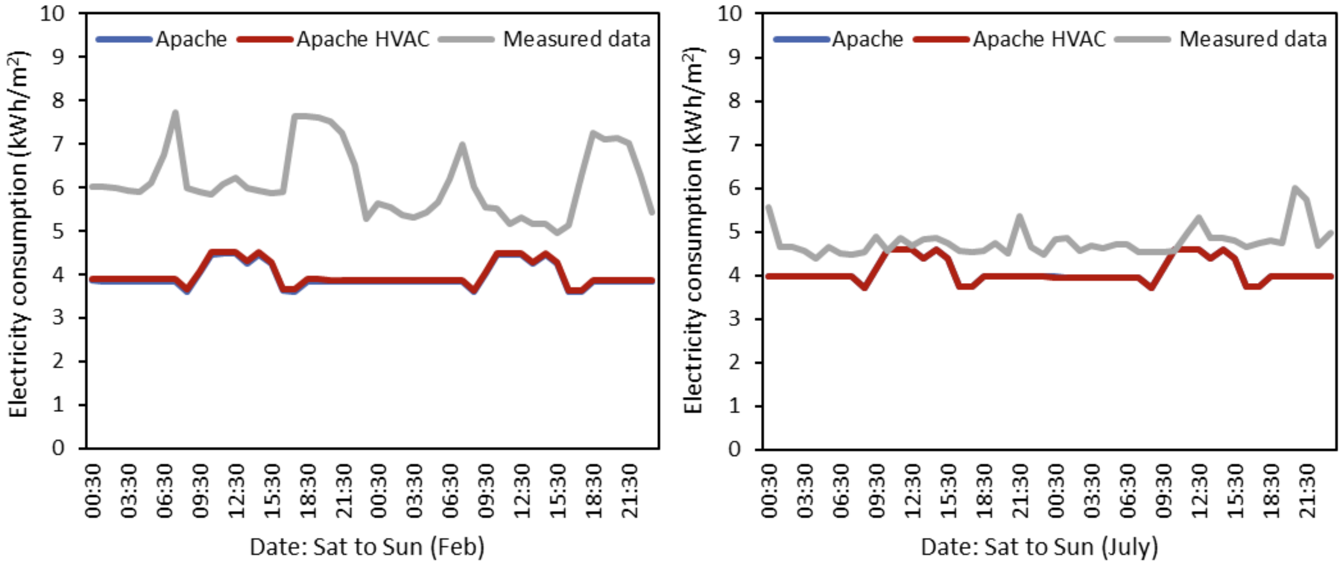

Figure 7. Hourly electrical demand during typical weekends in in winter and summer

1.2 Natural gas consumption

Figure 8 presents the simulated and actual natural gas usage throughout the year. Apart from holidays and the period that covered abnormal system operation in June, the fourth part (from 28th September to 7th December) was the only period that was entirely within term time. The simulation results of the Apache HVAC module for this period were almost identical to the measured data, but the predicted results of the Apache module were lower. At all other times, the predicted results for the use of natural gas showed significant differences from the actual data. There was also no regular pattern between the outputs of the two modules. Similar to the simulation results for electricity consumption, CVRMSEs that did not meet the calibration criteria implied the presence of error cancellation. However, as the actual gas consumption data lacked granularity on a monthly and half-hourly basis, it was less possible to identify the reasons for the modelling errors by analysing the unevenly large time spans.

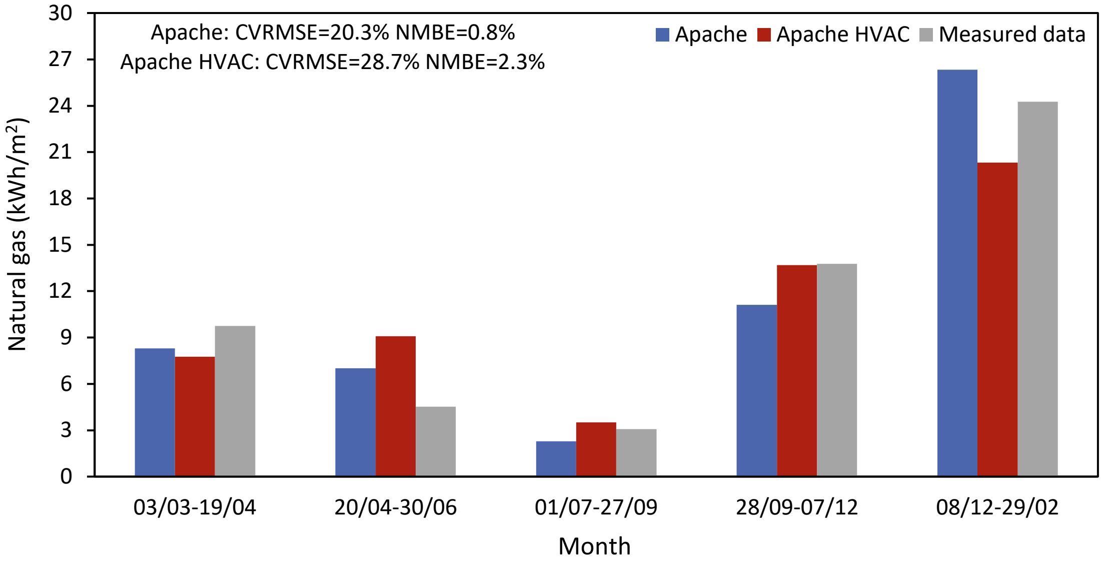

Figure 8. Simulated and actual Natural gas usage

2. Comparison of component level modelling

In order to analyse the underlying causes of the differences in the output of the Apache and Apache HVAC modules, it is necessary to compare their input parameters and calculation methods. For the electrical system, lighting and small power consumption were set up and calculated identically in both modules, the simulation of auxiliary energy and VRF systems was the source of the difference. The natural gas system served space heating and DHW, thus the simulation of the boiler was the main factor affecting the energy output. Therefore, this study focused on two components, the air handling unit (AHU) fans and the boiler.

2.1 AHU fans energy consumption

The Apache module only requires the Specific fan power (SFP) to be input for the AHU fan system. The SFP set for this modelling was 2.85 W/(l/s), which was calculated based on the actual technical specifications of the supply and extract fans in the AHU. This data represents the performance of the AHU fans system at full load. The calculation equation is shown below (DLUHC, 2021):

$$\text{SFP}=\frac{\text{Design fan power (sum of all fans in the ventilation system)}}{\text{Design flow rate}} \tag{1}$$

$$\text{Fan motor power consumption}=\text{Fresh air supply rate} \times \text{SFP} \tag{2}$$

The Apache HVAC module simulates the energy consumption based on user-defined performance parameters and curves for each fan under design conditions. The following equations are used to calculate fan motor power consumption (ASHRAE, 2016):

$$\text{Fan motor power consumption}=\frac{y(u)\Delta p^{D}V^{D}}{\eta_F^{D}\eta_M^{D}} \tag{3}$$

Where, V^D: Design flow rate (l/s), ΔP^D: Design total pressure rise (Pa), η_F^D: Design fan efficiency (%), η_M^D: Design motor efficiency (%), y_i: Fraction of design power.

When y_i=1, this represents the case where the fan is used at full load and the calculation result is the design fan power. Table 2 shows the link between the parameters provided in the fan specification and the parameters required in the two modules. Although the Apache HVAC module does not require the SFP to be entered, inputting the correct design flow rate and design fan power can ensure that the fans simulated by both modules have consistent SFPs under the design condition.

Table 2: The required input parameters and the design parameters provided in the technical specification.

<table>
<tr><th colspan="3">Technical specification</th><th colspan="2">Apache</th><th colspan="3">Apache HVAC</th></tr>
<tr><td rowspan="2">Design flow rate</td><td>Supply fan</td><td>6.45m^3/s</td><td rowspan="4">SFP</td><td rowspan="4">(9.04+9.37)/6.45 = 2.85 W/(l/s)</td><td rowspan="2">Design flow rate</td><td>Supply fan</td><td>6.45m^3/s</td></tr>
<tr><td>Extract fan</td><td>6.45m^3/s</td><td>Extract fan</td><td>6.45m^3/s</td></tr>
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<tr><td>Extract fan</td><td>9.37kW</td><td>Extract fan</td><td>9.37kW</td></tr>
<tr><td rowspan="2">Design total pressure</td><td>Supply fan</td><td>450Pa</td><td colspan="2" rowspan="6"></td><td rowspan="2">Design total pressure</td><td>Supply fan</td><td>450Pa</td></tr>
<tr><td>Extract fan</td><td>450Pa</td><td>Extract fan</td><td>450Pa</td></tr>
<tr><td rowspan="4">Total efficiency</td><td rowspan="2">Supply fan</td><td rowspan="2">58.5%</td><td>Fan efficiency</td><td rowspan="2">Supply fan</td><td>70%</td></tr>
<tr><td>Motor efficiency</td><td>83.58%</td></tr>
<tr><td rowspan="2">Extract fan</td><td rowspan="2">59.5%</td><td>Fan efficiency</td><td rowspan="2">Extract fan</td><td>70%</td></tr>
<tr><td>Motor efficiency</td><td>85%</td></tr>
</table>

This school building used the demand-controlled ventilation (DCV) strategy, which resulted in the SFP being constantly variable during actual system operation. According to previous studies and existing empirical equations, the variation in fan flow and the associated part-load fan power can be estimated based on occupancy levels (Burman *et al.*, 2014; ASHRAE, 2016). This in turn enables the SFP to be extrapolated.

$$\begin{cases} q = 0.5 \times q_{100\%} & \text{if } o \le 0.5 \\ q = o \times q_{100\%} & \text{if } o > 0.5 \end{cases} \tag{4}$$

$$P=0.0013+0.1470\times\left(\frac{q}{q_{100\%}}\right)+0.9506\times\left(\frac{q}{q_{100\%}}\right)^2-0.0998\times\left(\frac{q}{q_{100\%}}\right)^3 \tag{5}$$

Where, q: flow rate (l/s), $q_{100\%}$: flow rate at full load (l/s), o: Occupancy level (0–1), P: fraction of full-load fan power (0-1).

Occupancy level refers to the NCM standard profile, which was fine-tuned based on the actual occupancy schedule. According to equation (4), the average air supply during the occupied hours was 67.5% of the full load supply. Figure 9 presents the SFP variation due to DCV on a typical school day. The average SFP for the AHU fans on a typical school day was 2.11 W/(l/s). Since the Apache module does not have a setting that can specifically simulate DCV, it is reasonable to use the SFP derived from occupancy rates to simulate the energy consumption of the fans with the DCV strategy.

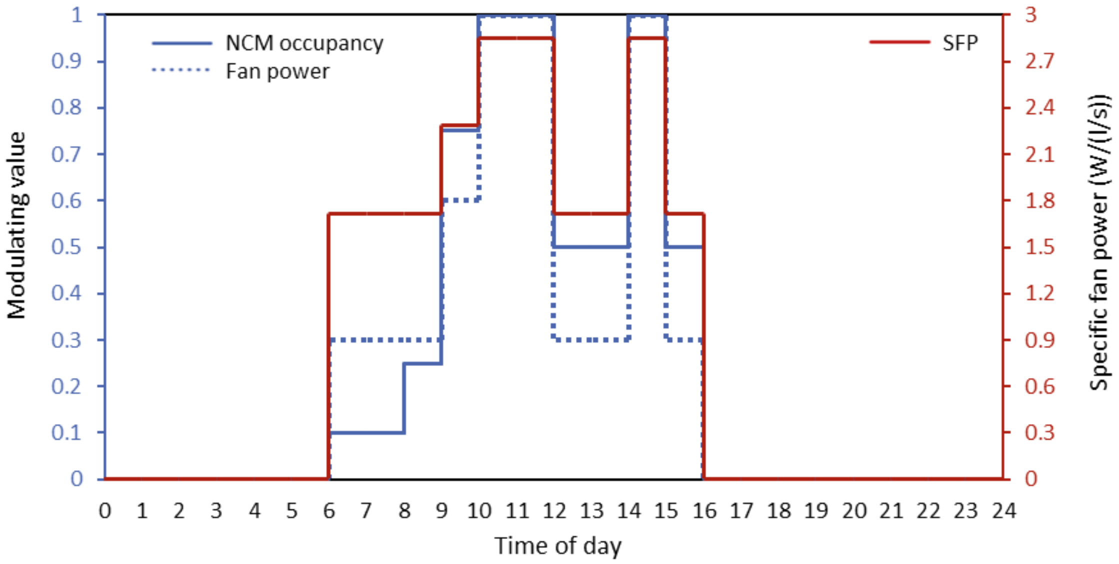

Figure 9. SFP variation due to DCV on a typical school day

The Apache HVAC module can be set up with CO_2 sensors to enable DCV and customise the minimum primary air supply. However, the default number of people provided by the NCM for each activity area causes the total number of simulated people to be three times that of the actual data, which leads to the diversity factor being introduced to bring the number of occupants into line with reality. However, the diversity factor is a static value, which results in a significant underestimation of the number of people in each room during peak occupancy hours. The model iteration revealed that the reduction in occupants caused the ventilation system consistently operated at the minimum flow set points in every room. In order to make the simulation scenario more realistic, an average air supply equivalent to the actual DCV operation should be estimated. Based on the previous extrapolation, it was assumed that the mechanical air supply to the zone heated by the radiant panels would be maintained at 67.5% of the design ventilation. The minimum primary airflow to the VRF system zone was maintained at the default 30% (ASHRAE, 2016). The software simulation results output the hourly system air flow rate and fan power, then calculated that the SFP was consistently maintained at around 1.78 W/(l/s). Figure 10 compares the SFP of the AHU fans in different simulations methods.

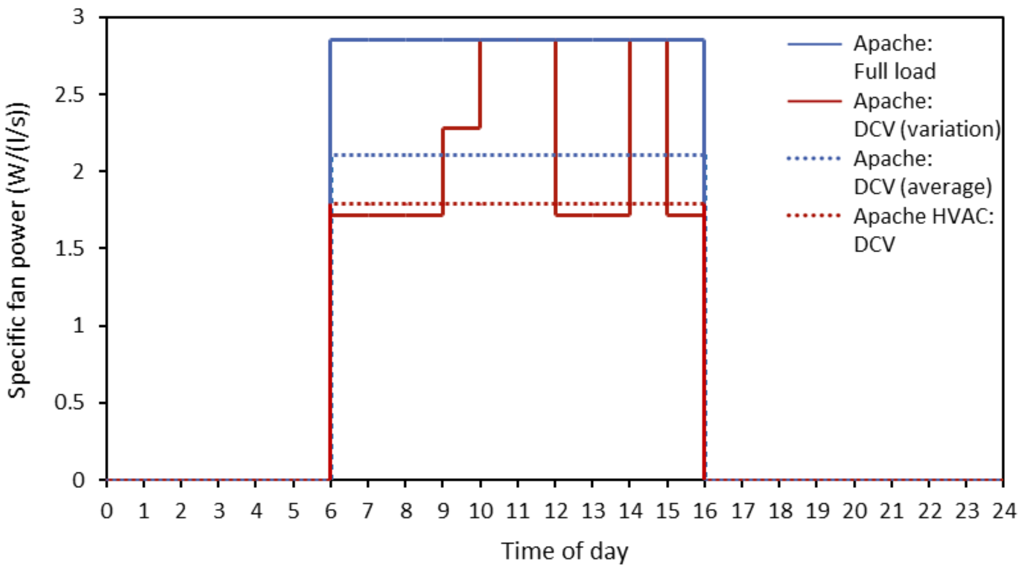

Figure 10. SFP of the AHU fans in different simulations methods

In addition, as the AHU specifications did not provide fan performance curves, this study assumed the use of the EDR Typical VSD Fan part load curve, which is predefined by the Apache HVAC module. Meanwhile, in order to analyse the impact of the performance curve settings on the prediction of fan energy consumption, the differences between the simulation results of the main variable speed drive (VSD) fan curve built into the software (Figure 11) and the measured data were compared. The simulation results of the AHU fan energy consumption for all scenarios with the Apache and Apache HVAC modules are shown in Table 3. The simulation results for the Apache module with DCV and the Apache HVAC module with the EDR typical VSD Fan curve were more in line with the actual energy consumption of the fan operation. The ideal fan, referring to the fan based on the theoretical Cube Law, led to the maximum simulation error due to the neglect of operational losses (Burman *et al.*, 2014; ASHRAE, 2016).

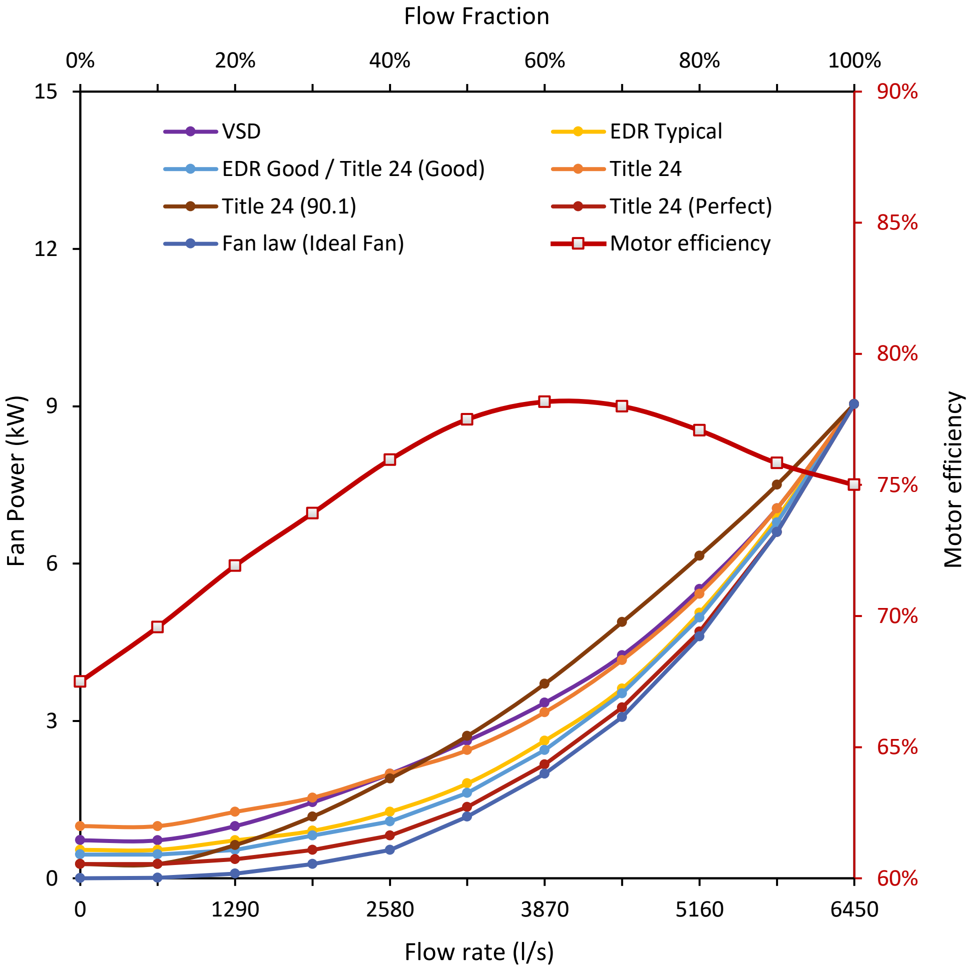

Figure 11. Performance curve of air supply fan

Table 3. Comparison of AHU fans energy consumption obtained by iteration of different performance curves and measured data

Fan types		AHU fans energy consumption (kWh/m^2/year)	Percentage differences from measured data
Methods	Measured data	2.52	
Apache	SPF=2.85	3.16	25.53%
	DCV: Average SPF=2.11	2.34	-7.07%
Apache HVAC	Variable-speed drive (VSD) fan	3.48	38.01%
	EDR Typical VSD Fan	2.29	-9.17%
	EDR Good SP Reset VSD Fan	2.00	-20.47%
	VSD with SP reset (Good) - Title 24	2.00	-20.47%

	VSD with SP reset (Prefect) - Title 24	1.58	-37.43%
	Any fan with VSD - Title 24	3.38	34.10%
	Any fan with VSD (90.1) - Title 24	3.43	36.25%
	Fan law (Cube Law Ideal fan)	1.14	-54.84%

2.2 Boiler Energy Consumption

In general, boiler energy consumption is the heating energy demand divided by the heating system efficiency. The Apache module requires the user to enter a static value for the seasonal coefficient of performance (SCoP) and the boiler seasonal efficiency, where SCoP refers to the heating system efficiency. The relationship between these two parameters is shown in Equation (6). The heat delivery efficiency is calculated automatically by the software. Therefore, it should be guaranteed to be less than 1 to take distribution losses into account.

$$\text{Seasonal coefficient of performance (SCoP)} = \text{Boiler seasonal efficiency} \times \text{Heating delivery efficiency} \qquad (6)$$

The Apache HVAC module allows input of detailed boiler parameters, and a range of built-in boiler types can be selected. The boiler operating efficiency is calculated as shown in Equation (7), which illustrates that the operating efficiency varies dynamically according to the heating load. Each boiler has the specific formula to calculate the part-load impact factor f_{Ept} (part-load ratio,T).

$$\text{Operating efficiency} = \text{Boiler rated efficiency} \times f_{Ept}\left(\frac{\text{heating load}}{\text{Rated heating capacity}}, T\right) \qquad (7)$$

Where, T: hot water supply (leaving boiler) temperature, and f_{Ept} (1, T) = 1.

The building was installed with condensing boilers. However, the post-occupancy evaluation found that the boiler had been operating in non-condensing mode and had a seasonal efficiency of 86% (Burman, 2016), which was used in the Apache module simulation. Based on this known information, the non-condensing boiler was selected for the simulation in the Apache HVAC module and the simulated result was 2% lower than the actual energy use. Besides, simulation tests were carried out for the performance curves of other boiler types. Table 4 compares the difference between the iteration results of different boiler performance curves and the measured data.

Table 4. Comparison of boilers energy consumption obtained by iteration of different performance curves and measured data.

Boiler types		Total natural gas (kWh/m^2/year)	Percentage difference from measured data
Measured data		55.30	
Apache	Seasonal efficiency: 86%	55.03	-0.49%
ApacheHVAC	Condensing Boiler	50.24	-9.15%
	Non-condensing Boiler	54.19	-2.01%
	Circa1975HighTempBoiler	54.12	-2.13%
	Circa1983MidTempBoiler	51.35	-7.14%
	NewerLowTempBoiler	50.71	-8.31%
	Virtual DES Heating	51.64	-6.62%
	Non-condensing Boiler - PLR	61.52	11.25%
	Condensing Boiler - PLR, Entering Temp	50.24	-9.15%

Discussion

For the annual energy consumption of the building, the simulation results of both the Apache and the Apache HVAC module were close to the measured data. However, the CVRMSE of the simulated results for both electricity and natural gas consumption did not meet the calibration criteria. Specifically, the lack of monthly and half-hourly actual data for natural gas made calibration difficult to perform. When the predictions were validated through different temporal granularity for electricity consumption, it was noticed that the usage curves calculated by the two simulation approaches were relatively close. In detail, the electrical simulation data for weekdays in winter was more accurate than for summer, which could be attributed to stable occupant behaviour and near-peak load operation of the HVAC system. In contrast, occupants may open windows more frequently for natural ventilation in summer, and the uncertainty caused by this random behaviour is difficult to properly set in the simulation. Besides, night schools and random activities caused the system to operate outside the normal schedule, which is difficult to estimate accurately.

For component level modelling comparisons, the Apache module could reliably estimate the electrical consumption of fan operation under DCV strategy by adjusting the SFP. However, the total amount of system air supply remains constant. In other words, the Apache module has no capability to respond to the effects of the DCV strategy on indoor CO_2 concentration and heating energy consumption. It only adjusts the simulation for auxiliary energy consumption. The Apache HVAC module can directly fine-tune the air supply percentage, which not only simulates the airflow delivered by the fans more reliably, but also gives feedback on the variation in indoor CO_2 concentration and heating energy consumption caused by different ventilation levels. However, using a static diversity factor to achieve the correct input for the total number of people would lead to consistently low CO_2 concentration, which makes the simulation of both the electrical demand for the fans and the heating energy demand inaccurate. Meanwhile, it can lead to an underestimation of cooling demand in summer. Therefore, to avoid the error caused by the diversity factor, the average air supply during the occupied periods was taken as the minimum primary air supply in this study, which was calculated by an empirical equation. Future research can consider using dynamic detection algorithms to replace the steady-state occupancy estimation used in this paper (Wang, Burnett and Chong, 1999). The occupancy profile can be estimated by monitoring the CO_2 concentration and imported into the simulation model (ibid.) Moreover, the sensitivity of the performance curves for fans and boilers to the energy consumption results was analysed in the Apache HVAC module, realising that unreliable efficiency settings can lead to significantly simulation errors. This illustrates the importance of extracting real parameters based on technical specifications, but the existing technical data sheets in the UK and Europe normally do not contain detailed performance curves for their equipment. On the other hand, there are differences between the actual operating performance curve and the design curve, and future performance modelling could consider using measured data to derive the operational performance curve of the equipment (Yin, Kiliccote and Piette, 2016).

Conclusion

This study developed both template level and component level building performance simulation modelling for a school building using two modules (Apache module and Apache HVAC module) in the IES VE software. The first key finding was that the annual energy consumption simulation results showed minimal discrepancies with the measured data, but the predicted results at the monthly and daily levels did not fully meet the calibration criteria. This indicates that using only yearly data to assess the accuracy of performance models may miss significant errors in the modelling input process. It is necessary to calibrate the model at a finer temporal granularity to prevent misinterpretation due to error cancellation. Secondly, when it comes to complicated control strategies, such as demand-controlled ventilation, detailed component-level HVAC modelling is more consistent with actual system operation than template-level modelling. Also, detailed modelling takes into account the impact of interactions between more input parameters on energy consumption. For example, Apache only considers the impact of SFP on auxiliary energy, but does not consider that the change in SFP is caused by variations in ventilation. Thirdly, the technical data sheets currently available in the UK and Europe are not consistent with the level of information required for detailed HVAC modelling. Further updates of information by equipment suppliers will facilitate the choice of component level modelling approach for building modellers.

Future work

Future research will introduce modeller and software variability into the study, because the personal preferences of modellers and the setting of detailed component levels in different model libraries are uncertain factors worth considering. The simple case in this paper will be used as a template to develop an exercise for practitioners. IES VE and Design Builder, both advanced simulation platforms, will be applied. Two separate groups of practitioners will be recruited for each software to model different levels of detail in HVAC systems. The input and output parameters of the two modelling approaches will then be compared with each other. A quantitative analysis of the results will be conducted to explore the underlying causes of the discrepancies and to discuss the selection of the optimal modelling approach. Furthermore, a questionnaire will be developed to obtain feedback from the practitioner's viewpoints to provide a qualitative analysis of the existing modelling challenges and the drivers of the variation in results. Eventually, the findings of the above study will be linked to larger-scale school buildings to improve the accuracy of performance modelling at stock level.

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