Can the choice of building performance simulation tool significantly alter the level of predicted indoor overheating risk in London flats?

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Abstract

The accurate prediction of building indoor overheating risk is critical in order to mitigate its possible consequences on occupant health and wellbeing. The Chartered Institution of Building Services Engineers issued Technical Memorandum 59 (TM59) with the aim of achieving consistency in the modelling processes followed for the prediction of overheating risk in new dwellings. However, as each tool's prediction may depend on its inherent assumptions, an inter-model comparison procedure was used to assess whether the choice of building performance simulation tool influences the overheating assessment. The predictions of two popular tools, *IES VE* and *EnergyPlus*, were compared for nine variations of a naturally ventilated, purpose built, London flat archetype, modelled under the default algorithm options. EnergyPlus predicted a high overheating risk according to TM59 criteria in seven out of the nine model variants, contrary to the low risk of all the IES VE variants. Analysis of heat transfer processes revealed that wind-driven ventilation and surface convection algorithms were the main sources of the observed discrepancies. The choice of simulation tool could thus influence the overheating risk assessment in flats while the observed discrepancies in the simulation of air and heat transfer could have implications on other modelling applications.

Practical applications Technical Memorandum 59 issued by the Chartered Institution of Building Services Engineers may be widely adopted within the industry to assist the prediction of overheating risk in new dwellings. This work suggests that the choice of building performance simulation tool can greatly influence the predicted overheating risk. Furthermore, the differences identified in the modelling of heat transfer processes could also impact other modelling applications. Following these results, the need for detailed empirical validation studies of naturally ventilated homes has been highlighted.

Introduction

Concerns over the accurate prediction and mitigation of indoor overheating in domestic buildings have recently intensified[1], mainly due to the unprecedented rate of global temperature increase associated with anthropogenic climate change[2]. As the external environment is an important driver of indoor conditions, an increase in the average and maximum ambient temperatures would translate to higher overheating risk in UK homes[3], with potentially adverse effects on the occupants' health and wellbeing[4], especially during periods of extreme heat episodes. Over the 10-day period of the catastrophic 2003 heatwave, an excess of more than 2,000 deaths were recorded in England and Wales[5]. During the same period, an increase of 74% in deaths in homes and 91% in care homes was estimated, with the domestic sector accounting for approximately 50% of the 15,000 excess deaths associated with the heatwave in France[6]. A meta-analysis estimated that currently 30% of the world's population is experiencing extreme levels of heat, a figure that may rise to 70% by 2100 if no action is taken to tackle climate change[7]. This would place the elderly and vulnerable (disabled or with long-term illnesses) most at risk[4,8,9].

To tackle these and other potential effects of climate change, international agreements aimed at reducing global carbon emissions have been negotiated[10]. Since 2008, the UK has pledged to reduce its CO_2 emissions by 80% below the 1990 baseline by 2050[11]. As the domestic sector has been responsible for a significant portion of the UK's energy use[12], there has been a significant drive to reduce its carbon emissions through measures such as the increase of building thermal insulation and airtightness[13,14]. However, strategies that focus on winter thermal comfort rather than whole-year building performance may inevitably lead to the

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unintended consequence of potentially increasing summer indoor overheating risk[15]. Therefore, efforts must be made to ensure that the low-energy newly built and refurbished homes will provide a thermally comfortable environment over the whole year.

The current guidance to meeting the UK Building Regulations recommends a steady-state modelling approach for the assessment of overheating risk in dwellings[13,16], which has been proven to consistently under-predict overheating[3]. To help ensure the design of healthy and thermally comfortable indoor environments, the Chartered Institution of Building Services Engineers (CIBSE) has released Technical Memorandum 59 (TM59)[17]. This guide aims at providing a common procedure for modellers and developers to quantify the overheating risk in new dwellings through the use of any Building Performance Simulation (BPS) tool that complies with the requirements of CIBSE AM11[17,18]. Such tools have dynamic thermal simulation capabilities, which allow them to predict indoor environmental conditions and other related parameters[19]. However, comparative tests such as the Building Energy Simulation Test (BESTEST) have revealed discrepancies in the modelling output of such tools[20–22].

As TM59 does not suggest a specific BPS tool, it is important to determine the implications of the possible differences on the predicted overheating risk. These may be quantified through structured inter-model comparison where the outputs of various BPS tools are compared under the modelling of the same building design[23]. Although such comparisons have been performed in the past[24–27], no study to date has focused on the prediction of overheating risk using the TM59 criteria. Therefore, this work may determine whether a modeller's choice of tool could significantly influence the overheating risk assessment.

The above discussion has motivated this research with the aim to identify and quantify the gap of overheating risk prediction in flat typologies, as they have been shown to be especially prone to overheating risk[28,29], due to the choice of BPS tool within the TM59 assessment. The two commonly used and widely validated[30–35] BPS tools used were: *EnergyPlus 8.7* and *IES VE 2016*.[36,37] Specifically, the aims of this study are threefold:

1. to discover whether statistically significant differences in overheating risk prediction of flat typologies exist between the two BPS tools under examination.
2. to investigate which algorithmic differences are responsible for any observed discrepancies in the prediction of overheating risk, and
3. to discuss the possible implications of the results on research, the construction industry and policy.

Given the recent release of CIBSE TM59, this work may initiate an early discussion regarding some of the assessment's uncertainties and identify appropriate actions prior to its widespread adoption.

Literature Review

High external ambient temperatures have long been associated with mortality and morbidity[38]. However, the modifying effect of the indoor environment on heat-related health effects is less well understood, with only a few epidemiological studies focusing on the impact of housing quality and indoor temperature on the risk of heat-related morbidity and mortality[4]. As people spend the majority of their time indoors, a comfortable and healthy environment is critical to human health and wellbeing[39]. Therefore, it is essential to identify and quantify factors contributing to indoor thermal discomfort.

Indoor Overheating Drivers

Research into overheating in homes has focused on understanding the drivers behind the high indoor temperatures with previous modelling studies being generally in good agreement. Higher thermal mass was found to lead to more stable temperatures and a decrease of overheating risk[40]. The dwelling's floor level was shown to be a key driver of overheating risk, with the likelihood of heat-related death increasing by 50% for the tallest buildings compared to the average in height buildings in London[28]. Similarly, a building's orientation has been demonstrated as a determining factor for overheating[41]. For dwellings experiencing similar external weather environment and occupant operation, high indoor temperatures were also correlated with internally positioned wall and floor insulation[42]. Controlled natural ventilation, especially night cooling, and external shading have been proven to be effective interventions to combat overheating[43,44].

TM59 Methodology

The issue of TM59 was motivated by the call of the Zero Carbon Hub[3] for consistent guidance on domestic overheating risk assessment. It acknowledges that thermal comfort is subjective but aims to provide a standard that precludes the worst levels of overheating in UK dwellings[17]. Internal load schedules, including heat gains associated with people, appliances and pipework, window and door operation were specified for modelling in BPS tools, along with two comfort criteria used to provide a pass/fail result[17]. During its development, the method was mainly tested on flats due to their high overheating risk potential, but should also be applicable to other typologies[17].

CIBSE's new methodology predicts a high risk of overheating for naturally ventilated buildings if any one of the two following exceedance criteria fail[17]:

1. The percentage of occupied hours where $\Delta T = T_{op} - T_{max}$ is greater or equal to $1\,°C$ during the period May to September, inclusive, should not exceed 3%.
2. Bedroom operative temperature should not exceed $26\,°C$ for more than 1% of the assumed sleeping hours (22:00-07:00) annually (equivalent to 32 hours).

Operative temperature (T_{op}) is the weighted average of the room's radiant (T_{rad}) and air temperature (T_{air}). Under the assumption of low air flow speeds, it is reasonable to assume that[45]:

$$T_{op} = \frac{1}{2}(T_{air} + T_{rad}), \tag{1}$$

T_{max} is the estimated maximum acceptable temperature according to the adaptive thermal comfort model[46,47]:

$$T_{max} = 0.33 \times T_{rm} + 21.8^{o}\text{C}, \tag{2}$$

where T_{rm} is the exponentially weighted running mean of outdoor ambient temperature. For a series of days, T_{rm} can be approximated using[46]:

$$T_{rm} = (1 - \alpha)T_{od-1} + \alpha T_{rm-1}, \qquad (3)$$

where α is a constant commonly taken as 0.8 while T_{od-1} and T_{rm-1} are the daily mean and running mean temperatures, respectively, of the day previous to the day of interest (T_{od}).

The first criterion is based on the European standard BS EN 15251[48] and stems from the adaptive principle[49] that people react in ways which tend to restore their comfort. This is captured through the term T_{rm}, which accounts for actions taken by occupants (such as the modifications of clothing level) to adapt to a change in temperature[46,49]. The field data underpinning this equation were collected in 26 European offices, under the EU Project Smart controls and Thermal Comfort (SCATs) project[45,50]. The applicability of a thermal comfort model derived from office based data in the domestic context may be questioned, while it has been suggested that factors other than temperature could also influence the level of comfort and tolerance to the thermal environment[51]. The second criterion was derived from research on sleep quality discussed by CIBSE in Guide A[47].

CIBSE acknowledges that TM59 is based on a number of assumptions[17]. One such assumption is the static temperature threshold used for window operation. This simplifies the modelling process of occupant behaviour, which has been characterised as one of the greatest uncertainties in building simulations[52,53]. A number of other factors besides air temperature have been identified to influence window operation[54]. In addition, it has been demonstrated that people perceive indoor temperatures and act to change their thermal comfort differently[9,55]. Two other implicit assumptions that fundamentally relate to the binary nature of the assessment and are not addressed in the guidance document are that: (a) the uncertainty of BPS tools and (b) the choice of BPS tool will not significantly alter the prediction. The former may be answered through empirical validation. The latter has motivated this work.

Methods

A schematic diagram of the inter-model approach is presented in fig. 1. This method was chosen as it allows for highly complex models to be directly compared[22]. However, it does not allow the modeller to identify which tool's prediction best reflects reality, something that may only be performed through empirical validation[21].

Model Development and Comparison

In the *Data Preparation* stage, a Base Case (BC) model based on a free-running, naturally ventilated, single aspect, top-floor flat created by another work was selected (fig 2a)[56]. The base case was chosen to be representative of a typical London flat, as they have been found to be particularly prone to overheating[28,29], and the design of TM59 focused on flat typologies[17]. The thermal properties of the building's fabric and windows, selected to represent those of a new-build, are summarised in table 1. Further to that:
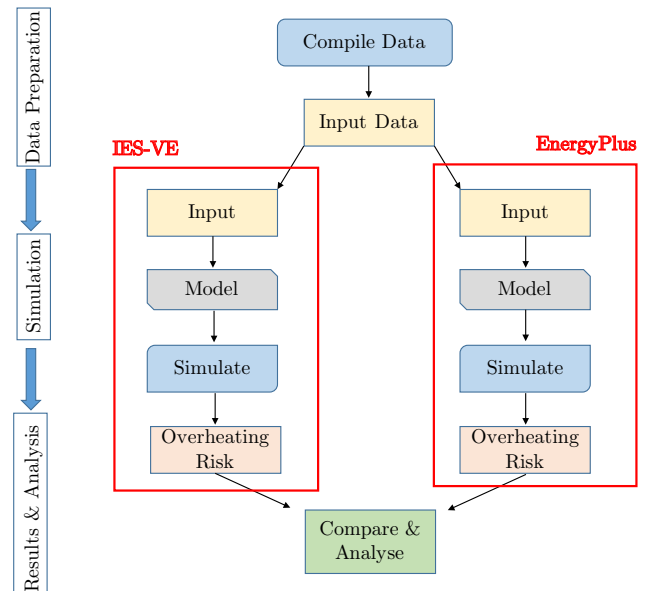
Figure 1. An illustration of the intermodel comparison approach used to determine differences in the overheating risk prediction between BPS tools.
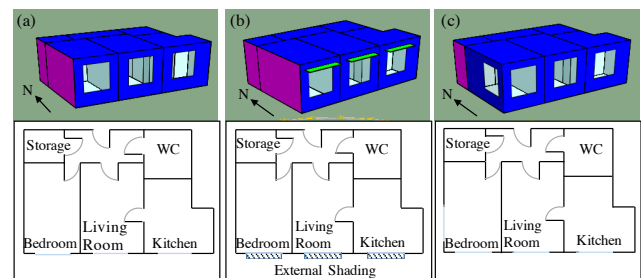
Figure 2. Illustrations of the base case (a), the model with external shading (b) and the dual aspect model (c).

- The Design Summer Year 1 CIBSE Weather File was used, as specified in TM59[17,57], with the location being the London Weather Centre.
- The internal gains for a two-person, double bedroom flat with separate living room and kitchen were modelled as recommended in TM59[17].
- Following TM59's instructions, windows were set to fully open when the internal air temperature exceeds 22 °C, is lower than the external dry bulb temperature* and the room is occupied (bedroom 00:00-24:00, living room/kitchen 09:00-22:00)[17].
- Doors (except the entrance and bathroom doors) were fully open between 08:00-23:00.
- Windows (and doors) were modelled as orifice openings (holes) with a discharge coefficient of 0.62. This simpler modelling approach eliminated the impact of their geometrical representation which could induce further inconsistencies and whose problems have already being discussed[58]. Therefore, only the

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*The requirement for the internal air temperature to be greater than the external dry bulb temperature was not explicitly stated in TM59. However, this an assumption that EnergyPlus automatically makes and IES VE was adjusted to match its operation.

differences in air flow equations may influence the predicted indoor environment.

Although the window operation has been questioned above, it was used as suggested by TM59 as it does not interfere with this work's aims.

In the *Simulation* stage, simulations for both BPS tools were performed with the same warm-up period of 35 days, using the same time-step of 10 minutes and a simulation period of a year.

Subsequently, in the *Results and Analysis* stage, the overheating risk was determined and compared between the two tools. This process was repeated for eight further model variations, created by varying the factors identified by the literature as being influential to overheating risk. Their properties are summarised in table 1. To assess the level of agreement between BPS tools, the null hypothesis that *the mean percentage of exceedance hours[†] predicted for each criterion across the model variations should be the same between tools at a significance level of 5%* was tested using the two-tailed Welch t-test of unequal variances[59].

A summary of the algorithm options used along with a brief description of their differences is displayed in table 2. Both tools offer a degree of flexibility in their modelling approach, especially EnergyPlus which offers a number of algorithm options for most heat transfer processes. However, the default algorithms were preferred in all cases as they are expected to be the most popular options within the modelling industry[60]. Thus, any observed differences should be representative of the typical levels of disagreement that could be found by professional modellers. Further information regarding the algorithms can be found in[61–63]. From equations 1, 2 and 3 and, it may be deduced that any differences in overheating risk observed will relate to the indoor air, radiant and external dry-bulb temperature. As both tools' approach to predicting the indoor conditions is based on a series of three heat balance equations[62,63], differences in the individual components of the balance equations will be responsible for any discrepancies observed in the indoor environment. The air heat balance, responsible for T_{air}, was the only case where all of the outputs could either be directly extracted from the tool or calculated from other variables. Therefore, to explain differences in T_{air} and the predicted overheating risk between tools, the following components of the air heat balance equation were compared: (i) Internal Convection, (ii) External Ventilation (iii), Interzone Airflow, (iv) External Infiltration and (v) Internal Gains. The comparison was performed for the discrete hourly time-steps that EnergyPlus predicted the BC bedroom to overheat but IES VE did not and may be summarised as:

$$\Delta Q_{i,j} = (Q_{i,j}^{IESVE}) - (Q_{i,j}^{E+}), \qquad (4)$$

where for each BPS tool, $Q_{i,j}$ is the heat transferred during the overheating hour i by heat process j.

Results & Discussion

Following the methods described above, nine models were constructed with the overheating risk predicted for each one. A summary of these predictions is presented in fig. 3 and

discussed in the following sub-section. Subsequently, the observed differences are interpreted through an analysis of algorithm differences between the two tools.

Inter-model Comparison
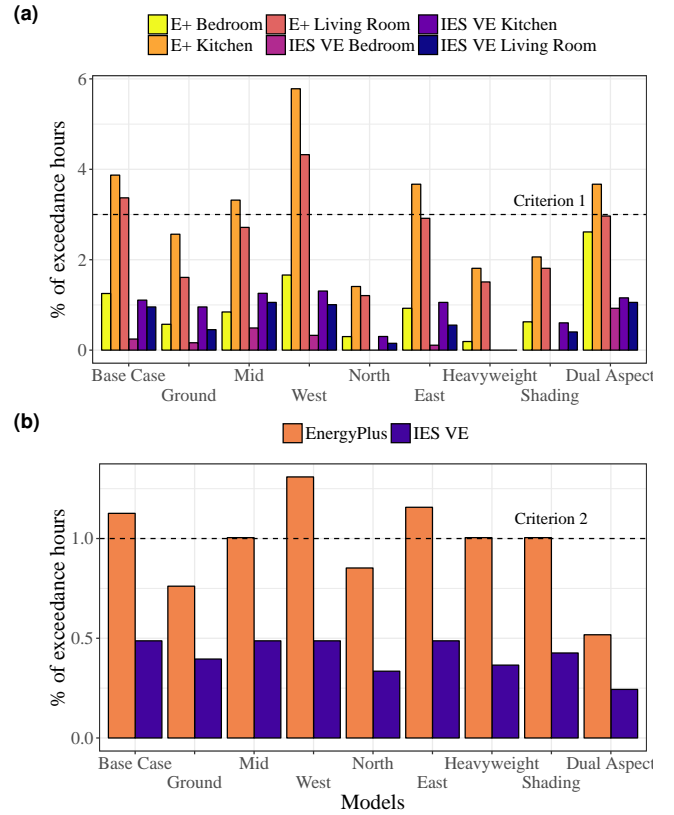
Figure 3. Part (a) compares the predicted overheating risk for Criterion 1 while part (b) compares the predicted overheating risk for Criterion 2.

From a simple observation of the overheating assessment presented in fig. 3, a greater number of overheating hours is predicted by EnergyPlus in comparison to IES VE. Overall, EnergyPlus predicts a high overheating risk in seven out of the nine cases. A low risk of overheating is predicted only for the ground floor and North-facing models, while the highest risk was associated with the West-facing, East-facing and base-case models. This is in accordance with existing studies in the literature which suggest that height and orientation can prove significant to the risk of overheating[28,41]. The hours of exceedance decreased significantly in relation to the base-case for the models with external shading and heavyweight construction while a marginal decrease of overheating hours relating to Criterion 2 was also observed, being again in agreement with the literature[40,44]. The addition of a secondary window in the dual aspect model led to increased solar gains, resulting in the doubling of the hours of exceedance within the bedroom. However, the percentage of sleeping hours (22:00-07:00) over which the operative temperature exceeds 26 °C halved. This is likely due to the

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[†]The percentage of occupied hours that either criterion threshold is exceeded.

Table 1. A summary of the key characteristics of the nine models developed.

Code	Description
BC	Floor level: $11.2\,\mathrm{m}$, orientation: south facing, single aspect, top level flat. Lightweight construction: Timber frame, external brick layer and internal plasterboard. U-values: Wall $0.17\,\mathrm{W/m^2K}$, window $1.28\,\mathrm{W/m^2K}$, floor $0.18\,\mathrm{W/m^2K}$, roof $0.13\,\mathrm{W/m^2K}$, Window Solar Heat Gain Coefficient - 0.5, Glazing Ratio - 0.3. Constant infiltration rate based on an air permeability of $5.0\,\mathrm{m^3/(h\,m^2)}$. Continuous added air exchange of $13\,\mathrm{l\,s^{-1}}$ for the kitchen and $8\,\mathrm{l\,s^{-1}}$ for the bathroom.
G	Ground-Level flat, floor level: $0\,\mathrm{m}$, flat of similar temperature above (adiabatic ceiling).
M	Mid-level flat, floor level: $5.6\,\mathrm{m}$, flats of similar temperature above and below (adiabatic ceiling and floor).
W	West-facing flat.
N	North-facing flat.
E	East-facing flat.
HW	Heavyweight construction with the same U-values as for BC: Concrete blocks, external brick layer, internal dense plaster and carpet.
SH	Shading: Overhang external shading, length of 2.2 m and width of 0.5 m over windows (fig. 2b).
DA	Dual aspect model with a second window included in the bedroom (fig. 2c).

Table 2. A summary of the simulation options used in the modelling process. h_c refers to the convection coefficient. * identifies the processes that are part of the air heat balance equation. Internal gains are not an algorithm option, but for EnergyPlus the occupant's radiant fraction can be altered while for IES VE it cannot.

Process	EnergyPlus	IES VE	Difference
Conduction	Conduction Transfer Function	Finite Differences with Hopscotch discretisation	Discretisation method
External Convection	DOE-2	McAdams Empirical	h_c depends on surface roughness, wind velocity and surface temperature for EnergyPlus. The h_c depends only on wind velocity for IES VE.
External Longwave	Default Blackbody	CEC based model	Different equations
Internal Longwave	Hottel's "Script F" model	CIBSE Mean Radiant	Different equations which relate to T_{rad}
Solar Distribution	Full Exterior	Default (Fixed)	Beam radiation incident only on the floor of EnergyPlus. Beam radiation distributed on surfaces according to angular characteristics for IES VE.
External Infiltration*	Ideal Loads Air System - Outdoor Air Supply	Air Exchange - Infiltration	Different Equations
External Ventilation* & Interzone Airflow*	Airflow Network	MacroFlo	Differences in the estimation of wind pressure coefficients & turbulence.
Internal Convection*	TARP	CIBSE Fixed	h_c depends on surface orientation and temperature for EnergyPlus. $h_c = 3.0$ for IES VE.
Internal Gains*	Default (Adjustable)	Default (Fixed)	Radiant fraction for people.

increased levels of ventilative cooling associated with cross-ventilation that allowed for the sufficient dissipation of heat accumulated during the day.

The models constructed in IES VE predicted a low risk of overheating in all nine cases. This was a result of the temperatures in IES VE models being consistently lower than in EnergyPlus, with a mean temperature difference of $0.6\,°\mathrm{C}$. The overheating levels were also less sensitive to perturbations of the physical model. As indoor temperatures are lower, they are not in near proximity to the overheating thresholds assessed. Changes in the gains or losses resulting from the alteration of the physical model may not cause a

Table 3. Summary of the statistical results (p-values and confidence intervals) which examined the null hypothesis of similar mean percentage of exceedance hours between tools.

Room	Criterion	P-value	95% CI [%]
Bedroom	1	0.02	0.144-1.34
Living Room	1	0.0004	1.05-2.68
Kitchen	1	0.0007	1.21-3.32
Bedroom	2	0.00005	0.373-0.743

sufficient increase in temperature to impact the overheating assessment. Notably, the trends in predicted exceedance hours between the models slightly vary between the tools. Using Criterion 1, the bedroom's predicted percentage of overheating hours decreased from 1.3% for the base case (top-floor flat) to 0.8% for the mid-level flat according to EnergyPlus. For IES VE, the same metric increased from 0.2% for the base case to 0.5% for the mid-level flat.

The above comparisons have revealed statistically significant differences in the predictions of overheating risk between the BPS tools, as demonstrated by table 3. For a significance level of 5%, there is enough evidence to reject the null hypothesis, suggesting that the mean percentage of exceedance hours predicted by each BPS tool differ for a 95% confidence level. For Criterion 1, the smallest difference is observed for the bedroom, with a p-value of 0.02 and the lower end of the confidence interval (CI) of 0.144%. For the same criterion, the differences increase for the living room and kitchen. For Criterion 2, the p-value was 0.00005 while the CI ranged between 0.373% and 0.743%. The following sections aim at investigating the factors responsible for the observed differences in greater depth.

Heat Transfer Comparison

Key weather parameters such as wind speed, wind direction, dry bulb temperature and external solar irradiance onto the South-facing wall were compared and found to be in good agreement ($R \geq 0.997, R^2 \geq 0.994$). Consequently, it is highly unlikely that the predicted differences are a result of each tool's interpretation of the weather file.

To determine the reasons for the differences in zone air temperature, a comparison of the air heat balance's components was performed as described in the previous section. The results are presented in fig. 4, with key descriptive statistics summarised in table 4.

Two patterns may be seen in fig. 4a, suggesting that the importance of certain components depends on the state of the model. For approximately half of the hours the external ventilation rate is zero in both BPS tools, due to the windows being closed, leading to a perfect agreement. Over this period, surface convection and inter-zone airflow are the most important factors for the observed differences. In the case that significant discrepancies in external ventilation are recorded, the differences in surface convection increase in magnitude. A possible explanation could be that ventilative cooling leads to a lower zone air temperature, which subsequently forms a stronger temperature gradient for convective heat transfer. This exacerbates the already existing deviations in the modelling of surface convection. Overall, surface convection and external ventilation dominate the differences with absolute

mean values of $47.4\,\mathrm{W}$ and $39.9\,\mathrm{W}$ respectively. External infiltration had the smallest contribution, followed closely by internal gains. Given that internal temperatures were consistently higher for EnergyPlus, a difference in external infiltration was expected. A further breakdown of the internal gains revealed that the default way by which each BPS tool assigns the convective to radiative ratio of occupancy related gains was responsible for the observed differences.

A slightly different picture is observed in the comparison of heat transfer differences when EnergyPlus predicts a failure of Criterion 2 and IES VE does not (fig. 4b). For 13 out of the 21 occurrences, surface convection is responsible for more than 66% of the total heat rate difference, dominating with an absolute mean value of $85\,\mathrm{W}$.

The investigation of volumetric flow rate within the bedroom of the base-case model in fig. 5a (with key statistics in table 5) revealed fluctuations between minima and maxima until 10:00 for IES VE. This is a result of the window being modelled as continually alternating between an open and closed state due to the internal temperature being very close to the threshold of $22\,^{\circ}\mathrm{C}$. Similar modelling takes place for EnergyPlus as well, but is not clearly seen here[‡]. The frequent overnight window operation is unrealistic and the predicted overheating risk could be different if windows were modelled as being closed overnight, an assumption which may be true for about one in five occupants[42].

While windows are modelled as closed (14:30-19:30), the door flow rate between the two BPS tools are in close agreement, with IES VE predicting a mean influx of $76.1\,\mathrm{l\,s}^{-1}$, close to EnergyPlus's mean value of $81.2\,\mathrm{l\,s}^{-1}$. This indicates a similar modelling of the temperature-dependent stack effect, the only air flow mechanism available at this point, while the slightly higher flow rate of EnergyPlus is associated with its higher indoor temperatures.

When windows are modelled as open for both tools (10:30–13:30), the mean window influx predicted by IES VE was $231\,\mathrm{l\,s}^{-1}$ compared to $130\,\mathrm{l\,s}^{-1}$ predicted by EnergyPlus. The relative agreement between tools on stack-driven airflow discussed before suggests that wind-driven ventilation may be responsible for the significant discrepancies observed. This was further supported by the near linear relation displayed between the wind speed and the volumetric flow rate predicted by IES VE, but not by EnergyPlus (fig. 5a). To explore this hypothesis, the weather file was altered on the specific day by setting the wind velocity to zero with the results shown in fig 5b. Window influx between the two BPS tools now appears to be in significantly closer agreement, with mean percentage difference of 11% compared to 56% recorded before. The greater volumetric flow rate predicted by IES VE, led to a greater ventilative cooling which is visible as the difference in external ventilation heat transfer in fig. 4a. By looking at the equations relating to natural ventilation of either tool, it is hypothesised that the observed discrepancies in

[‡]EnergyPlus' *Airflow Network* module runs independently of the simulation timestep and operates the window at a higher frequency based on extrapolated temperature between timesteps. The printed result in fig. 5a is the average over each time step and hence the very high frequency of window operation is not visible.

(a)

(b)
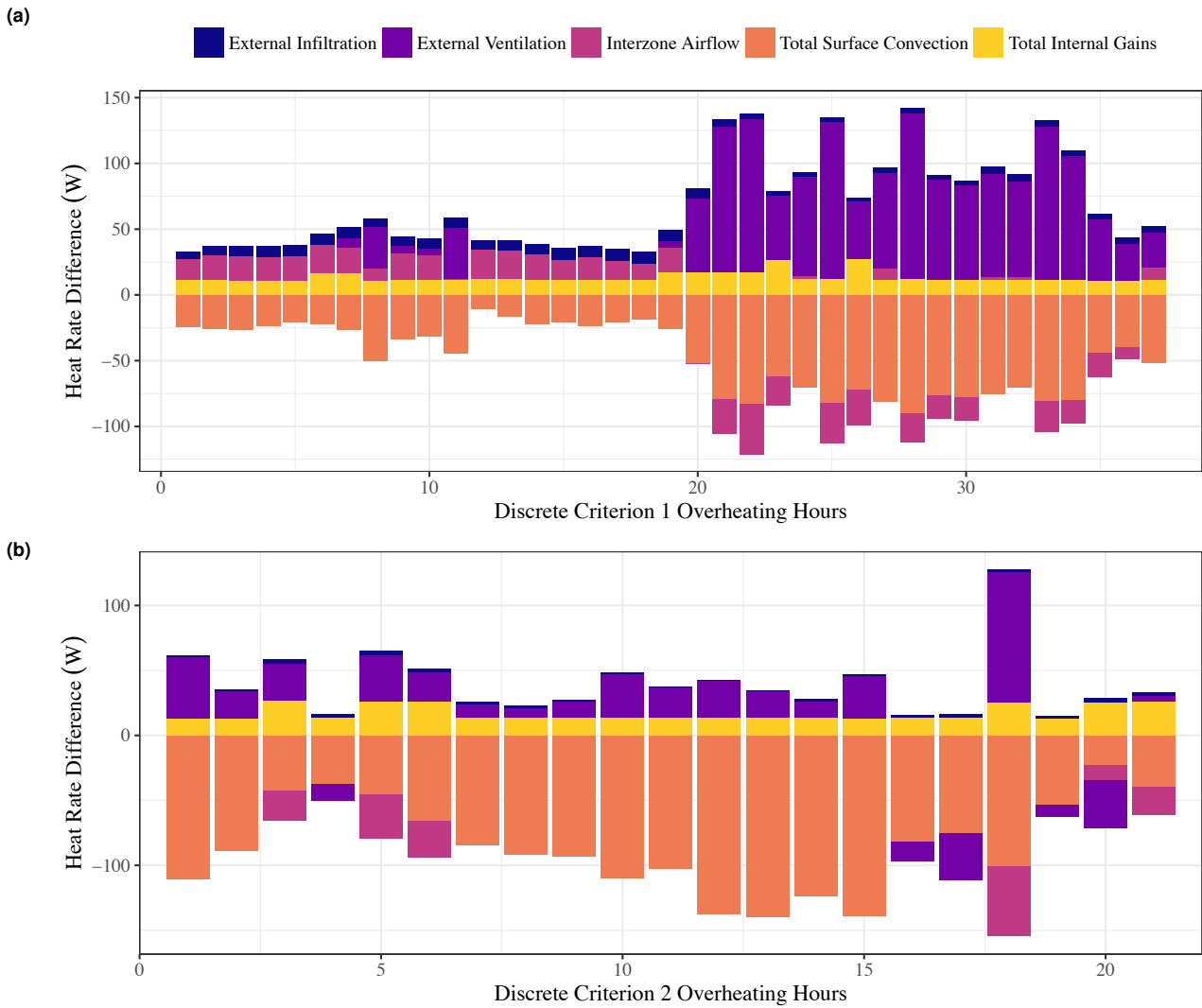
Figure 4. Bar charts displaying the differences between air heat balance components of the two tools for selected hours. The differences were estimated during hours that overheating was predicted by EnergyPlus but not IES VE, by subtracting the EnergyPlus heat transfer component from the IES VE component. External Infiltration refers to the heat transfer related to constant supply of outdoor air while External Ventilation is the heat transfer associated with air flow through the windows. Part 4a presents these differences for the 37 discrete hours that differences were determined for Criterion 1, while part 4b is the equivalent comparison for 21 occurrences for Criterion 2.

Table 4. Summary of the key descriptive statistics of the heat flow differences displayed in fig. 4.

	Criterion 1				Criterion 2			
Process	Mean (W)	SD (W)	Max (W)	Min (W)	Mean (W)	SD (W)	Max (W)	Min (W)
External Infiltration	6.00	2.06	8.73	2.81	1.78	0.92	3.24	0.359
External Ventilation	39.9	43.1	126	0.00	26.0	29.5	99.8	-36.5
Interzone Airflow	16.6	18.6	22.8	-38.7	8.17	15.0	0.00	-53.5
Total Surf. Conv.	47.4	25.6	-10.5	-90.0	85.0	35.5	-22.9	-139
Total Internal Gains	13.3	3.88	27.3	11.0	17.2	5.89	27.1	13.1

Table 5. Summary of the mean flow rates presented in fig. 5 for the normal and altered weather file over two time periods: Windows open (10:30-12:00) and closed (14:30-19:30).

		Door Influx			Window Influx		
Wind	Windows	E+ ($l\,s^{-1}$)	IES VE ($l\,s^{-1}$)	% Dif.	E+ ($l\,s^{-1}$)	IES VE ($l\,s^{-1}$)	% Dif.
Normal	Open	33.6	38.2	13	130	231	56
Normal	Closed	81.2	76.1	-6.5	0.00	0.00	0.0
Zero	Open	33.4	51.3	42	133	118	11
Zero	Closed	81.8	66.1	-21	0.00	0.00	0

the modelling of wind-driven ventilation are the result of differences in wind-pressure coefficient options and the modelling of wind turbulence between the two tools[58,61,62].

(a)

(b)
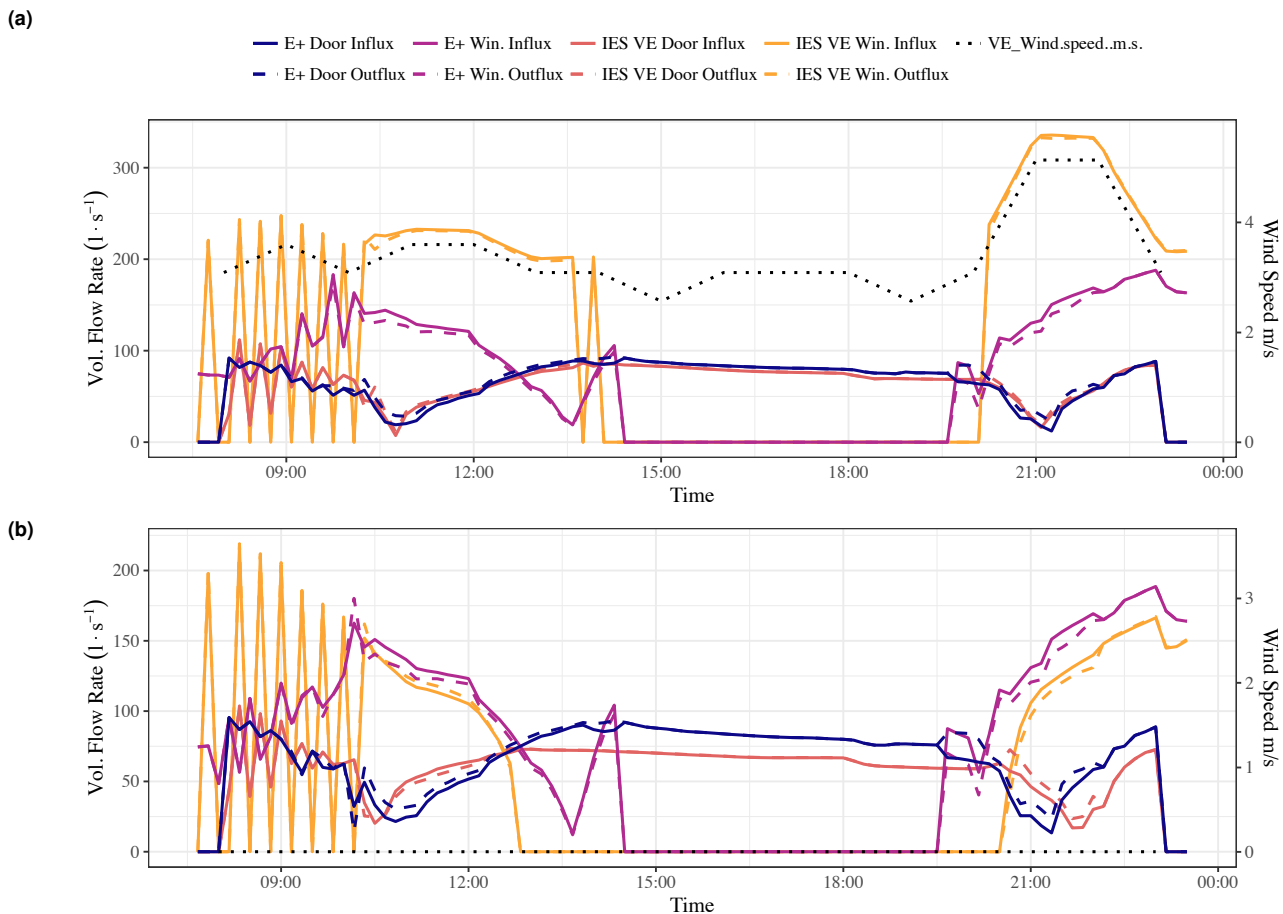
Figure 5. Line graphs of the predicted volumetric flow rate for the bedroom door and window in either BPS tool on the 15th of July. Part 5a is the comparison with the suggested weather file. In part 5b the wind velocity was set to zero.

To understand the significant differences of surface convection shown in fig. 4, a comparison of the individual components that influence this mechanism was performed (figure 6). The driving factor for the differences appears to be the higher surface temperature predicted by EnergyPlus, as visualised in fig. 6c. The subsequently greater temperature gradient displayed in 6d is able to overcome the lower convective heat coefficient (fig. 6b) and result in an overall greater convective heat flow demonstrated in fig. 6a. A further exploration into the reasons behind EnergyPlus' higher surface temperature could not be performed due to a lack of detailed output by IES VE and the incompatibility of output between tools. Similarly, a clear quantitative comparison of other mechanisms suspected to differ and discussed in table 2 could not be achieved.

Limitations

The most significant limitation of the present study was the inability to empirically validate either tool. Therefore, it is impossible to determine which tool is more accurate. In the light of the observed discrepancies, it will be important to empirically validate the two tools to determine their predictive ability in the context of indoor overheating prediction. Contrary to the typical validation experiments that have been performed in the past, natural ventilation should be one of the key variables being tested[32,33].

Another critical limitation was the restricted number of outputs, mainly from IES VE, that would provide an insight

in the different approaches of modelling heat mechanisms. An important example was the lack of outputs relating to longwave radiation exchange between surfaces, which directly influences the room's radiant temperature and overheating risk[63].

A final limitation was the focus on a single typology modelled at the same location and with the same weather file. Quantifying the level of discrepancies across multiple typologies, locations and weather files could provide a more complete picture of the differences that may arise from the choice of BPS tool. However, as the archetype model used in this study represents the typology that has been identified to be especially prone to overheating risk[28,29], the key question of whether the choice of BPS tool could influence the assessment's predictions has been answered for the most vulnerable case.

Implications

Within the industry, the exact prescription of certain physical inputs included within TM59 along with the specified threshold criteria allows for a consistent method of assessing indoor overheating risk in residential buildings. However, as demonstrated above, the choice of BPS tool can impact the predicted level of overheating risk in London flats. As both tools examined in this work have been thoroughly tested[30,31], a strong argument that supports a single tool may only be formed through the thorough empirical validation of its algorithms for a wide range of dwelling typologies,
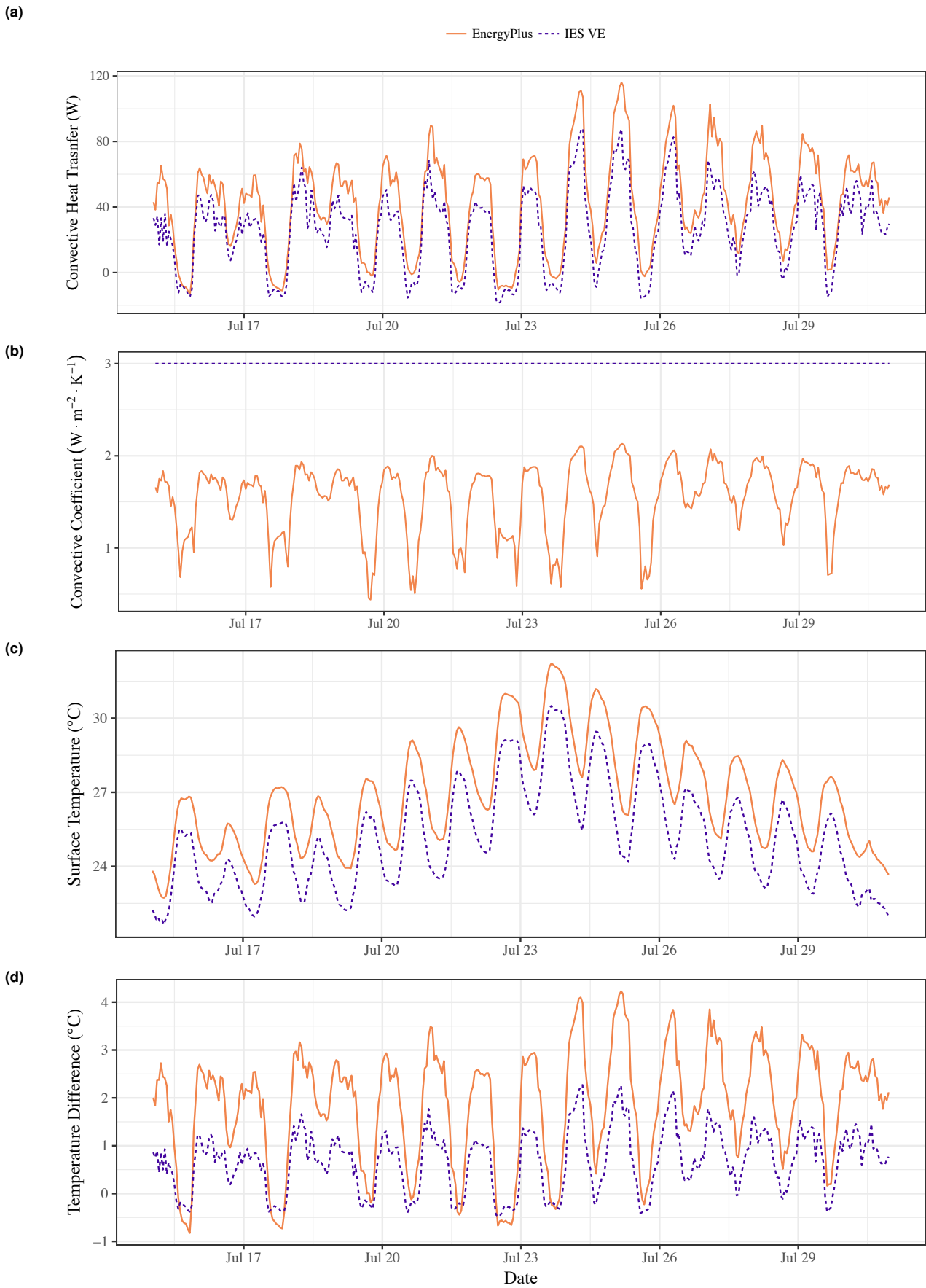
Figure 6. Plot 6a is a comparison of the convective heat transfer from the east-facing bedroom wall to the zone air. Plot 6b compares the convective heat coefficients while plot 6c compares the surface temperatures for the same wall. Plot 6d compares the temperature difference between the wall's surface and zone air temperature. For EnergyPlus the *adjacent air temperature* was used as suggested by [64].

climatic settings and occupancy scenarios. Until such work is performed, a question arises on why modellers put their trust on their tool of choice. Multiple reasons may come to mind, such as ease of use, familiarity or cost. A possible cause of concern may be that modellers choose their tool based on their ability to easily pass any required assessments. Furthermore, provided the great number of algorithm options found within each tool, the degree of manipulation that this choice may allow can be questioned[65]. With the occupant's health in mind, it may be advisable to choose a tool that predicts the worst-case scenario for the intended assessment. For example, as EnergyPlus also predicted higher temperatures in the winter, IES VE may provide the worst case scenario for a free-running building during the heating season. However, further comparative work is required for each assessment before concluding to such a decision. Overall, the industry can benefit from the use of TM59 as a standardised method of assessing the effect of interventions on reducing the overheating risk.

For the academic field, a need for more detailed empirical validation work and improvement of the available BPS tools is apparent. Research is required to identify and quantify the uncertainties that may accompany the predicted overheating risk. In addition, reconsidering the approach of predicting overheating risk may also be beneficial. Existing empirical validation studies which do not account for natural ventilation identified differences of 1–$2\,°C$[32,33,35]. This level of uncertainty is sufficiently high as to alter an overheating risk level from low to high, impairing the prediction's accuracy.

From a policy perspective, although this work identified a significant level of uncertainty in the overheating assessment methods suggested by TM59, BPS-based assessment may still be considered better than the current approach described in Appendix P of SAP[16]. The use of a steady-state approach with mean input values by Appendix P prevents it from investigating future weather predictions with extended periods of high temperatures. Beyond prediction, policy may pursue the enforcement of interventions whose effectiveness has already been established, such as external shading[44]. The building regulations may impose such measures on new dwellings most at risk, such as top-floor or West-facing flats. With the projected increase in external temperatures due to ongoing climate change, this action may prove critical if we are to prevent the uptake of air-conditioning, which could significantly increase the energy demand and associated building carbon emissions.

Conclusions

This work aimed to quantify and understand the differences in the overheating risk prediction between two commonly used building performance simulation tools, EnergyPlus 8.7 and IES VE 2016. This was achieved through an inter-model comparison of nine variations of a naturally ventilated, London flat archetype, following the overheating risk assessment described in the Technical Memorandum 59. The default algorithm options were selected in either tool to represent what is expected to be the most popular choices within the modelling community. Significant differences were recorded between predictions, with the EnergyPlus

models recording a high overheating risk in seven out of the nine cases, while IES VE predicted a low overheating risk for all models. Within each tool, the factors expected to influence the risk of overheating such as height, orientation or shading agreed to a satisfactory level with the literature.

This work also set out to identify which heat mechanisms are responsible for the discrepancies in overheating risk for the base-case model. A dominant factor was determined to be the modelling approach of natural ventilation, with IES VE predicting in certain cases double the volumetric flow rate compared to EnergyPlus. In particular, wind-driven ventilation and the effect of turbulence appear to be driving the observed differences in the modelling of natural ventilation. Another factor that dominated the predicted differences was the internal surface convection which resulted from the higher surface temperatures predicted by EnergyPlus. Although specific parameters that could be contributing to these higher surface temperatures were examined, a definite conclusion could not be drawn due to the lack of all the required outputs and black-box nature of IES VE.

The precise magnitude of differences in overheating cannot be generalised to other models or tools. However, this work presents evidence that the choice of BPS tool could influence the assessment for London flats which are expected to be highly susceptible to overheating risk. Following these results, a number of implications have been identified and discussed.

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