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A case study on the impact of fixed input parameter values in the modelling of indoor overheating

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Abstract. Global efforts to reduce greenhouse gas emissions from buildings while also improving their environmental resilience have intensified. These efforts are often supported by building stock models which can inform policymakers on the impact of policies on energy consumption, greenhouse gas emissions and the indoor environment. The input values of such models are commonly informed by reference tables, which can result in inaccurate specification and incomplete representation of the distribution of possible values. In this modelling case study of a semi-detached dwelling archetype, the influence of using a reference U-value $(2.1\,\mathrm{W/(m^2K)})$ for solid walls in England on heat-related mortality rate is compared to a probabilistic specification based on empirical evidence (median = $1.7\,\mathrm{W/(m^2K)})$). Using the theoretical reference U-value generally resulted in a lower indoor overheating risk compared to the use of the empirically derived U-values pre-retrofit, but a larger increase in heat-related mortality rate following internal wall insulation $(1.20\,\%)$ than the use of the empirical median $(0.94\,\%, 95\,\%)$ Confidence Interval = $0.87-0.99\,\%$). This highlights the potentially significant implications of using fixed reference values. Future work will employ this probabilistic framework on multiple influential parameters.

1. Introduction

In the latest report by the Intergovernmental Panel on Climate Change (IPCC), anthropogenic global warming had reached approximately 1 °C above the pre-industrial levels in 2017, with an approximate rate of increase of 0.2 °C per decade following the year 2000 [1]. The increase in ambient temperature, driven by the continued growth of greenhouse gas (GHG) emissions, poses a severe risk to global health and wellbeing. To mitigate the worst consequences of climate change, there is a sustained effort in multiple countries around the world to reduce GHG emissions across multiple sectors. As part of this effort, the United Kingdom (UK) has set the goal of reaching net zero by 2050, requiring major reductions in GHG emissions [2]. Even with the best efforts, ambient temperature along with the frequency and severity of heatwaves will continue to increase, exacerbating the already existing problem of summer indoor overheating in the UK [3]. It is, therefore, vital to integrate efforts to reduce the environmental impact of buildings with adaptation measures that safeguard the occupants' health and wellbeing.

Building stock models can provide a tool for policymakers towards the identification and adoption of effective climate change adaptation and mitigation measures. Often, such modelling endeavors rely on the use of building physics tools that require detailed specification of building, occupancy and climate characteristics. *Archetypes* are often used to simplify the modelling task when modelling at the city, regional or national scale. Archetype-based models are where simple

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building definitions are used to represent a group of similar dwellings [4]. An archetype-based, bottom-up engineering approach can be further differentiated into two classes; *stochastic* and *deterministic* [5]. In the deterministic approach, fixed model inputs are used often not based on empirical data. This approach will, therefore, henceforth be referred to as theoretical. Stochastic approaches sample model input from probability distributions. In the stochastic approaches, parametric uncertainties are propagated to output variables, capturing the lack of knowledge about influential model parameters. In addition, they enable a more accurate representation of building parameter diversity – the value of a model input may vary between the dwellings that the archetype represents. However, a stochastic approach requires a large number of simulations per archetype resulting in a larger computational burden than the deterministic approach.

A common modelling input for building simulations is the external wall U-value, frequently treated as a fixed model input and often informed by Appendix S of the UK Government's Standard Assessment Procedure (SAP), also referred to as Reduced Data SAP (RdSAP) [6]. SAP is the UK Government's National Calculation Methodology for assessing the energy performance of dwellings, with RdSAP used for existing dwellings. RdSAP provides reference tables that a modeller can use to infer building properties based on a dwelling's age and construction type. During fieldwork led by the Building Research Establishment (BRE), the U-values of approximately 300 walls were measured in England, including 80 standard solid walls [7]. Wall U-values were estimated from heat flux measurements taken by affixing heat flux plates (Hukseflux HFP01) on the internal wall surface whilst trying to avoid thermal bridges. Following the initial publication of the results, it was discovered that the heat flux plates read 4-8% lower than intended [8]. After an adjustment of 6%, measured U-values for solid walls were found to have a median of 1.69 W/(m²K) (and a standard deviation of 0.32 W/(m²K)), 24 % smaller than the theoretical value of 2.1 W/(m²K) [8]. Some reasons behind this possible discrepancy have been explored by Li et al. [9]. This discrepancy meant that the assumed energy performance of solid wall dwellings is likely better than previously considered, and planned installations of solid wall insulation would result in relatively lower energy savings across the retrofitted residential stock. [7, 9, 8]. Following this study, BRE released an update of RdSAP in 2017 advising the use of 1.7 W/(m^2 K) as the U-value for solid wall constructions.

Several building stock models have relied on the use of RdSAP reference tables, including the solid wall U-value of $2.1~\rm W/(m^2 \rm K)$, for energy use, indoor air quality and overheating assessment [10, 11]. This work aims to investigate the possible implications of this misspecification for indoor overheating risk and associated heat-related mortality rate. A solid-wall semi-detached model is used as a case study to compare the deterministic approach (U-value fixed at $2.1~\rm W/(m^2 \rm K)$) with the stochastic approach informed by empirical evidence. Models are simulated both preand post- retrofit, where retrofit consists of the installation of 100 mm of internal wall insulation. The differences between central values will be discussed, along with the significance of using a distribution instead of a single point as a model input.

2. Methods

The following sections describe the model used for this study, the output of interest and the use of confidence interval.

2.1. Model Specification

This study deploys a metamodelling framework developed by Symonds et al. [12]. The metamodel consists of a set of neural networks trained on a large number of EnergyPlus v.8.8.0 simulations. The EnergyPlus models, generated by an in-house tool written in Python, represent the English housing stock using an archetype approach. Eight building typologies, considered as the most representative within the English housing stock, were defined within the model [10]. In the most recent version of the metamodelling framework, a modeller can choose amongst

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Table 1. Continuous model inputs specified for this study. Orientation refers to the angle of the primary facade East of the true North.

No.	Parameter	Value	Source
1	Fabric permeability	$11 \text{ m}^3/\text{hr/m}^2$	[17]
2	Orientation	0°	-
3	Window opening temp.	$22~^{\circ}\mathrm{C}$	[18]
4	Roof U-value	$0.67 \text{ W/(m}^2\text{K})$	[6, 19]
5	Window U-value	$3.10 \text{ W/(m}^2\text{K})$	[6]
6	Floor U-value	$0.70 \text{ W/(m}^2\text{K})$	[6]
7	Glazing Fraction	0.26	[19]
8	Floor-ceiling height	$2.60 \mathrm{\ m}$	[19]
9	Floor area (per storey)	$51.6~\mathrm{m}^2$	[12]
10	Internal gains	4 MWh	[12]
11	Solar Absorptance	0.9	[20]

three construction types, two occupancy types and specify the values of up to 13 continuous variables relating to a building's fabric properties, space heating, equipment and window use. The metamodel outputs metrics relating to indoor air quality, heating demand, standardised indoor temperature and summer overheating.

A solid wall semi-detached typology, located in the West Midlands region of England was modelled. An occupancy profile that assumed the continuous presence of two pensioners who open their windows during the summer months depending on the indoor temperature and the time of the day was selected [12]. It was also assumed that the heating system was off during the summer months. The values of all relevant continuous model inputs are provided in Table 1. For the deterministic approach, a theoretical wall U-value of $2.1\,\mathrm{W/(m^2K)}$ was assumed, based on the 2014 update of RdSAP [6]. For the stochastic approach, 300 simulations were run based on samples drawn from a distribution fitted to the corrected empirical data provided by Hulme et al. [7, 8]. For both approaches, the simulations were repeated by assuming the installation of 100 mm of internal wall insulation (glass fiber layer with a density of $80\,\mathrm{kg/m^3}$ and thermal conductivity of $0.04\,\mathrm{W/(mK)}$). The internal wall insulation was assumed to only influence the external wall U-value, with no other change in the building's characteristics.

2.2. Overheating Output

The overheating output of interest is the Mean of the Maximum Daytime Temperature (MMDT) for the living room, calculated for days when the two-day rolling mean of the maximum outdoor temperature exceeds the heat mortality threshold for the region. The rationale behind this metric relates to epidemiological relationships derived by Armstrong et al. between daily counts of all-cause mortality and predictors based on daily ambient temperature between the summers of 1993 to 2006 in 10 government regions in England and Wales [13]. Their analysis quantified a threshold T_{heat} , the 93rd centile of the two-day rolling mean of the maximum outdoor temperature, over which there is an increase in mortality with increase in temperatures in all governmental regions except the North-East. The region chosen for this analysis was West Midlands, England, with a threshold of 23 °C and a population-average, heat-related increase in Relative Risk (RR) of 2.2%/°C past the threshold. Since no such empirical relationship between indoor temperatures and relative risk exists, it was assumed that on days that the external temperature threshold was exceeded, the temperature-mortality relationship was the same for indoor temperatures as

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for outdoor temperatures [14]. The modelled difference of MMDT (Δ MMDT [°C]) due to the retrofit for an average summer day exceeding the mortality threshold was translated into a heat-related change of Relative Risk (Δ RR [%]). This was calculated by multiplying Δ MMDT with the region-specific increase in relative risk per degree Celsius past T_{heat} (Δ RR/ Δ T [%/°C]):

$$\Delta RR = \Delta MMDT \times \Delta RR/\Delta T \tag{1}$$

$$= (\text{MMDT}_{post} - \text{MMDT}_{pre}) \times \Delta RR/\Delta T \tag{2}$$

where $MMDT_{pre}$ and $MMDT_{post}$ are the MMDT pre and post-retrofit respectively.

2.3. Confidence Intervals

To determine whether the difference in wall U-value, MMDT and ΔRR between the empirical median and theoretical values were significant, 95% confidence intervals (95% CI) were used. The empirical median is based on a sample of 80 dwellings and may differ from the population median (if all solid wall dwellings were monitored). To quantify this uncertainty and test whether the theoretical value is statistically different to the empirical median, a 95% confidence interval (95% CI) was estimated around the median using parametric bootstrap (5000 repetitions). A confidence interval is an estimate of the range of values which is likely to include the unknown population median [15]. The use of 95% CI formally assumed that if repeated random samples were taken from population, the estimated confidence intervals would include the true population median 95% of the time [16].

3. Results

Histograms for solid wall U-values pre and post-retrofit are shown in Figure 1. For the pre-retrofit group of dwellings, there is large spread of U-values, with an interquartile range of $0.42\,\mathrm{W/(m^2K)}$. The theoretical U-value of $2.1\,\mathrm{W/(m^2K)}$ lies outside the 95 % CI of $1.59-1.76\,\mathrm{W/(m^2K)}$ estimated for the empirical median, at the 93rd percentile of the pre-retrofit distribution. With the 95 % CI of the differences in theoretical and empirical U-values ranging between $0.34-0.51\,\mathrm{W/(m^2K)}$, the theoretical value is therefore different to the empirical median at a significance level of 95 %. The spread of U-values following retrofit is only a fraction of the pre-retrofit variation, with an interquartile range of $0.02\,\mathrm{W/(m^2K)}$. The addition of internal wall insulation reduced the theoretical U-value from $2.1\,\mathrm{W/(m^2K)}$ to approximately $0.34\,\mathrm{W/(m^2K)}$, while the same energy efficiency measure reduced the empirical median from $1.69\,\mathrm{W/(m^2K)}$ to $0.33\,\mathrm{W/(m^2K)}$.

Based on the U-values shown in Figure 1, the MMDT was estimated and is visualised in Figure 2. The positively skewed distribution of pre-retrofit MMDT has a range of 0.6 °C and an interquartile range of 0.14 °C. Using the theoretical U-value results in an under-prediction of the MMDT for approximately 91 % of all models. The difference between the empirical median and theoretical value is 0.12 °C, with a 95 % CI of 0.10–0.15 °C. Post-retrofit, the narrow distribution of U-values, in comparison with pre-retrofit, results in a narrow distribution of MMDT with an interquartile range less than 0.01 °C. Figure 3(a) illustrates the change in MMDT following retrofit. For the prediction based on the theoretical value, there is a 0.54 °C increase in MMDT which is 0.12 °C larger than the 0.42 °C (95 % CI: 0.40–0.45 °C) increase for the empirical median. The distribution of Δ MMDT suggests that the relative increase in mortality risk will depend on the initial U-value which is highlighted in Figure 3(b). The increase in relative risk due to the increase in MMDT associated with retrofit is 0.94 % (95 % CI: 0.87–0.99 %) for the empirical median, 0.26 % lower than the prediction of 1.20 % based on the theoretical U-value.

4. Discussion

This study investigated the influence of solid wall U-value specification within building simulation models on estimated indoor overheating risk. A deterministic modelling approach,

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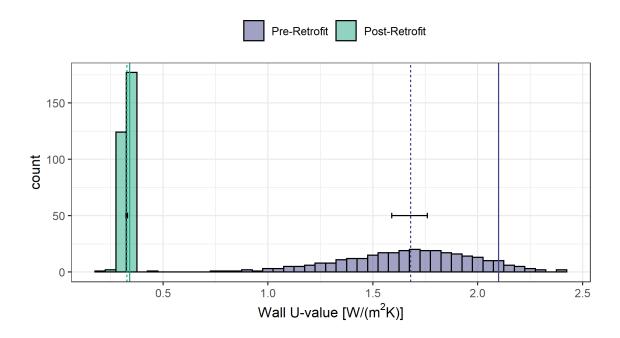


Figure 1. Histograms of wall U-values pre and post-retrofit. The dashed (---) and solid (—) lines represent the empirical median and theoretical U-values. The error bar demonstrates the 95% confidence interval of the empirical median.

with a single theoretical input was compared to a stochastic approach where inputs were sampled from a probability distribution based on empirical data collected in England by BRE [7].

With the theoretical wall U-value being statistically different to the empirical median, one focal point of discussion is the inaccurate specification of a central value. By assuming that the empirical median is the closest estimate to the true central value of solid walls in England, the building fabric heat loss is likely less than previously assumed. Previous work discussed the impact that this might have on the real energy savings from solid wall insulation [8, 9]. This modelling study looked at the possible consequences of such misspecification on indoor overheating risk. The risk in solid wall dwellings is likely higher than previously considered. This does not change the heat-related mortality of the un-retrofitted building stock. However, it does imply that occupants of solid wall dwellings may be at slightly higher overheating risk than previously assumed – whether this is the case will depend on the true values of other building parameters which were not examined in this analysis. With the installation of solid wall insulation, the differences in U-values diminish (approximately $0.01 \,\mathrm{W/(m^2 K)}$) as thermal resistance is dominated by the insulating material's properties. This results in a negligible difference in MMDT post-retrofit, suggesting similar levels of overheating risk. Therefore, the contribution of solid wall insulation to the increase in heat mortality risk would likely be less in reality than if the theoretical value was used.

A second point for discussion relates to the use of a stochastic or deterministic modelling approach. Lack of empirical data to inform this model inputs, enables a stochastic approach to provide an uncertainty around the assumed central values. Whilst distributions will likely differ from the distribution of real values, it can allow modellers to study the impact of model input miss-specification on the output of interest (e.g. space heating demand or indoor overheating). In some cases, the process of identifying why the central value can vary and by how much can in itself inform the modelling process. Beyond capturing the uncertainty around the central

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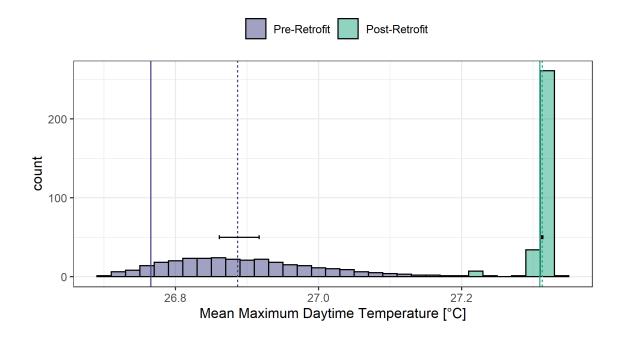


Figure 2. Histograms of the predicted Mean Maximum Daytime Temperature (MMDT) for a building modelled with pre and post-retrofit wall U-values. The dashed (---) and solid (—) lines represent the MMDT associated with the empirical median and theoretical wall U-values. The error bar demonstrates the 95 % confidence interval of the empirical median.

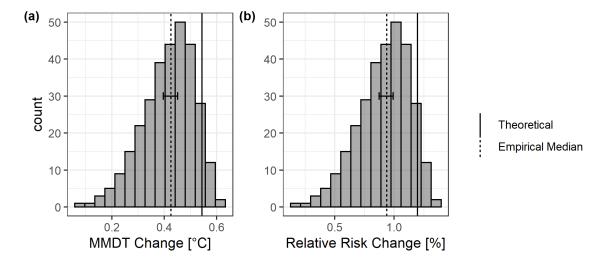


Figure 3. Distributions of the changes of Mean Max Daytime Temperature (a) and associated heat-related change in relative risk (b) following the installation of solid wall insulation. The error bars indicate the 95 % confidence interval of the empirical median.

value, a stochastic approach may also represent the diversity of building parameters within the stock. Although dwellings with solid wall construction may be modelled by a single archetype, there is a spread in wall U-value, which suggests that some occupants may be at a higher indoor overheating risk than others. If done holistically, where variation of all influential parameters is

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captured together with occupant vulnerability and microclimate, it can inform the prioritisation of indoor overheating interventions.

4.1. Implications

The findings of this work have implications for modelling practices in academia and industry. Modelling inputs should be based on empirical evidence where possible. Even widely used theoretical values may prove inaccurate. The impact that such inaccuracies will have depends on the sensitivity of model outputs on the inputs. In addition, a stochastic modelling approach should be preferred over a deterministic approach for influential model inputs that may be uncertain or vary – a form of sensitivity analysis can identify the influential inputs.

The outcomes of this work may also inform the approach of policymakers. Considering the results of this case study, solid wall dwellings on the left tail of the U-value distribution would ideally be prioritised for indoor overheating interventions but not for solid wall insulation. This does not mean that they should not be retrofitted but that they would benefit less than dwellings on the right tail of the distribution. Following the installation of solid wall insulation, the difference in MMDT and associated heat-related mortality rate are likely negligible. Therefore, post-retrofit all dwellings would have equal priority of receiving an intervention to reduce summer overheating. It should be highlighted that this study only examined solid external walls; in practice, the impact of all other parameters that might influence energy use and heat related mortality should be accounted for. However, this case study demonstrates an approach that could be used when considering other variations within the building parameters.

4.2. Limitations

This modelling task focused on the influence of a single model input on indoor overheating and compared it to the use of an empirically-based probability distribution. For all other model inputs, fixed values were used based on theory or empirical-evidence where possible. This choice was made to simplify the modelling task. A complete treatment of the impact of fixed theoretical values would sample probabilistically from all influential model inputs whose value is unknown or variable. In addition, it was assumed that the installation of internal wall insulation only influences the wall's thermal transmittance. Whilst this is likely the greatest impact that wall insulation has on building's heat flow, other parameters such as infiltration, will also change.

5. Conclusions

In this paper, the indoor overheating risk was predicted for a pre-retrofitted, solid wall, semidetached dwelling archetype in two ways: (i) Assuming a fixed wall U-value from the 2014 update of Reduced Data Standard Assessment Procedure (RdSAP), (ii) By sampling from an empirically-derived probability distribution of solid wall U-values. The models were then adapted by assuming the installation of 100 mm of internal solid wall insulation (SWI) and the simulations were repeated. Based on the results, it is likely that non-retrofitted solid wall dwellings are currently at a higher risk of indoor overheating than previously thought. There is also likely a spread in summer indoor temperatures of solid wall dwellings which is partly due to the diversity of wall U-values found within this construction type. Following retrofit, the range in summer indoor temperatures reduced to a level that indicates an equally high risk of indoor overheating regardless of each dwelling's exact pre-retrofit wall U-value. In addition, the relative increase in heat related mortality due to installation of SWI is smaller (0.94 % vs 1.20 %) if the empirical median U-value is used over the theoretical RdSAP derived value. Since the above conclusions are based on modelling case study, caution should be used when generalising the results. Future work will assess the influence of multiple uncertain parameters on indoor overheating.

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