Placement of monitors for quantifying indoor air pollutant exposure in UK homes: issues for consideration

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Abstract

Monitoring indoor pollutant concentrations is integral in the efforts to improve indoor air quality in UK homes. The impact that the number and placement of monitors can have on the quantified pollutant exposure is an under-researched, yet potentially important consideration. To address this research gap, this work employed an EnergyPlus-CONTAM co-simulation approach to model fine particulate matter ($PM_{2.5}$ – indoor- and outdoor-sourced) and radon in four UK archetype homes: semi-detached, mid-terrace, bungalow, and low-rise flat. Using data from only one or two locations in each home led to discrepancies in the estimated exposure, with root mean square errors reaching 600% for $PM_{2.5}$, and 119% for radon. Collecting whole-house data should be pursued, whilst generalising from a limited dataset should be done with caution.

Keywords Indoor Air Quality, Sensor Placement, Pollutant Exposure, Co-simulation, Monitoring

1. Introduction

Exposure to environmental air pollution is a leading driver of morbidity and mortality (1). It has been causally linked to an increased risk of several illnesses, including respiratory and cardiovascular diseases (2). Over recent decades, the monitoring of outdoor air pollution together with the introduction or improvement of standards and regulations has resulted in a decline in the emissions of pollutants with probable impacts on health (3). Efforts to reduce air pollutant concentrations indoors have not progressed as rapidly as those focused on outdoor air pollution (1,4), despite the impacts on global mortality being comparable according to the World Health Organisation (WHO); out of 6.7 million deaths attributed to air pollution in 2020, 3.2 million were thought to be the result of exposure to household air pollution (5).

Part of the challenge in developing standards to improve indoor air quality is the currently limited understanding of how air pollutant concentrations vary over space and time, within and between buildings (6). Improving our understanding requires wide scale and long-term monitoring of several pollutants for a diverse and representative set of buildings (7). This is especially important as we transition to better insulated buildings on our road to Net Zero. Changes to the airtightness and ventilation of buildings, and homes in particular, may have positive and negative effects on indoor air quality and health (8). Thus, monitoring of indoor air at the initial stages of this transition is crucial for avoiding locking in adverse effects, especially for the most vulnerable (7).

An important consideration when monitoring indoor air quality is the number of sensors to be used and their placement (9,10). Modelling and empirical work on sensor placement within non-domestic buildings has offered valuable insights. Optimal sensor placement for an office setting, investigated by Yun and Licina through controlled chamber experiments, was shown to depend on the pollutant being investigated (9). A Computational Fluid Dynamics (CFD) approach was used to explore sensor placement within a laboratory room (10). Despite a growing body of research on the impact of sensor placement in monitoring indoor air, work that focuses on sensor placement within UK homes is lacking. In response to this research gap, this paper explores the effect that the number and location of sensors can have on quantifying pollutant exposure.

The concentrations of two air pollutants, particulate matter with aerodynamic diameter of 2.5 μm or less ($PM_{2.5}$) and radon, were simulated in four common archetype models of UK homes: a semi-detached, a mid-terrace, a bungalow, and a low-rise flat. Pollutant exposure was estimated for up to four occupants for each archetype, by considering the time assumed to be spent in each room based on previously published profiles. This exposure was compared against an approximate exposure; estimated using subsets of the data to represent the exposure that would be estimated if only some of the rooms were being monitored. Section 2 provides further information on the modelling framework and methods of estimating and comparing pollutant exposure. The results are presented and discussed in Sections 3 and 4, respectively.

2. Methods

A CONTAM-EnergyPlus co-simulation framework, capable of simulating indoor temperature and pollutant concentration in UK housing archetype models, was employed in this research. The characteristics of the archetype models and pollutants are summarised in Sections 2.1 and 2.2, respectively. An in-depth description of the modelling framework, is offered by Wang et al. (11).

2.1 Archetype characteristics

The layout of the four archetype models, presented in Figure 1, is based on work by Oikonomou et al (14). To limit the factors that vary between models, the U-values of the building fabric and airtightness of the four archetypes were assumed to be the same, as shown in Table 1. All four models were assumed to be constructed of solid walls with single-glazed windows and solid floor. The flat was assumed to be located on the ground floor.

Figure 1 – Floorplans for the four archetypes.

Characteristics	**Mid-terrace**	**Bungalow**	**Semi-detached**	**Flat**
Air permeability ($m^{-3} h^{-1} m^{-2}$ @50Pa)	15			
Wall U-value ($Wm^{-2} K^{-1}$)	1.7			
Window U-value ($Wm^{-2} K^{-1}$)	4.8			
Floor U-value ($Wm^{-2} K^{-1}$)	1.2			
Loft U-value ($Wm^{-2} K^{-1}$)	0.4			N/A
Roof U-value ($Wm^{-2} K^{-1}$)	2.3			N/A
Floor Area (m^2)	142	89	92	54

Table 1 – Building characteristics (12,13)**.**

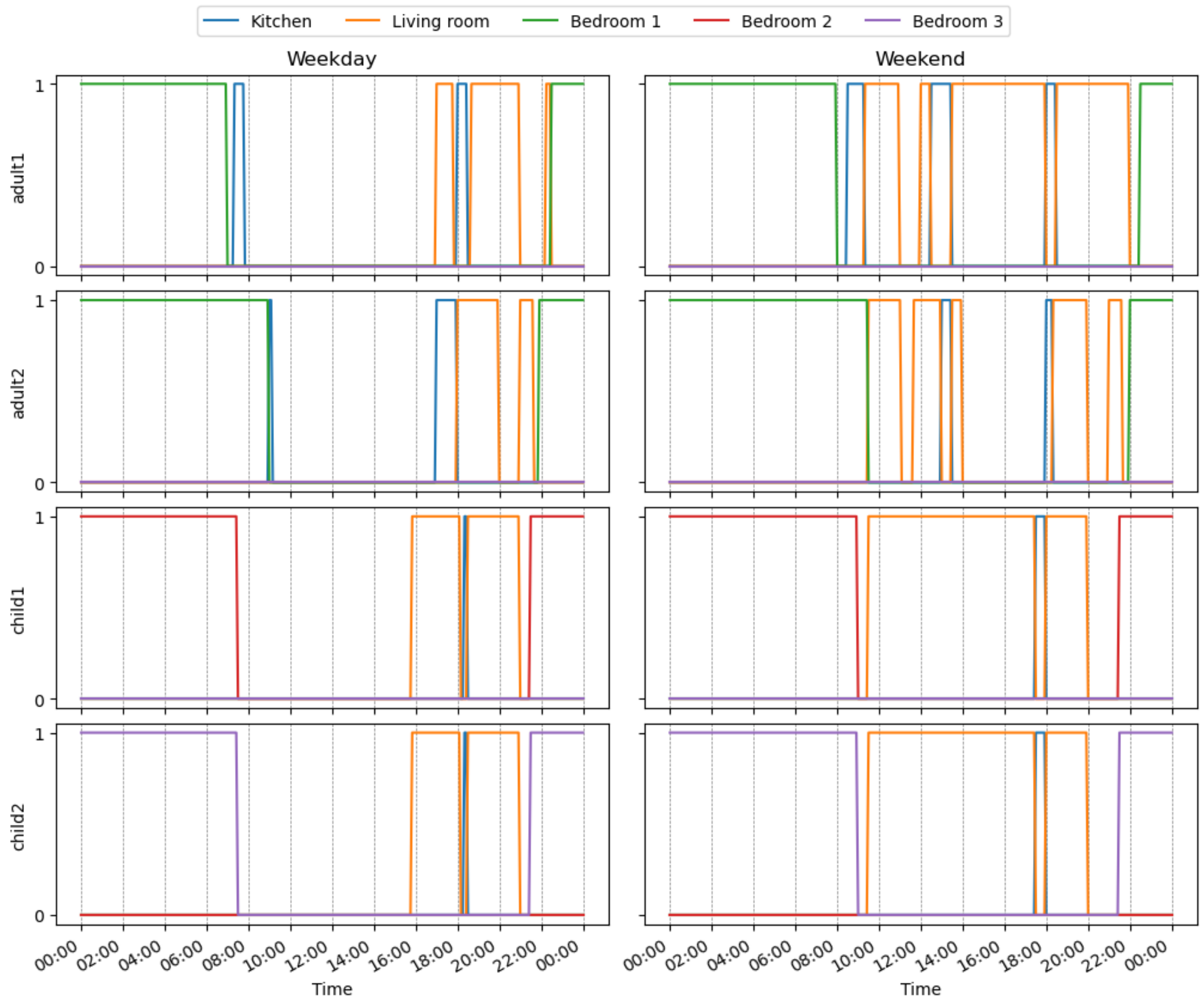

Figure 2 – Modelled hourly occupancy profiles for a typical weekday and weekend day. The y-axis represents the proportion of time spent in each room.

All four archetypes were assumed to be naturally ventilated. Intermittent extract fans were modelled in the bathroom and kitchen, with the minimum extract rate as specified by Approved Document F of the Building Regulations 2010 (15). During the summer period, windows in the living room and bedrooms were modelled as open during occupied hours (Figure 2) if the indoor temperature exceeded 22 °C (16). The windows in other rooms were modelled as open during the daytime but closed at night. During the heating season, windows were modelled as closed, except in the kitchen and bathroom were open during cooking or showering. Heating was modelled using simple electric radiators and with a thermostat set point of 22 °C (17). Internal doors were constantly open except for: (i) the kitchen door during cooking, (ii) the bedroom doors overnight, and (iii) the bathroom and loo doors during use.

Occupancy profiles developed in previous work were used in this study (17). The mid-terrace and bungalow houses were assumed to be occupied by two adults and two children (Figure 2). Both adults were assumed to sleep in bedroom 1, while each child was assumed to sleep in a separate bedroom. Adult 1 was modelled as spending more time in the kitchen during cooking activities than other occupants. The semi-detached house was assumed to be occupied by two adults (bedroom 1) and one child (bedroom 2). For the one-bed flat, only the two adult occupants were modelled. The presence profiles of the occupants in the semi-detached house and flat were the same as those in the mid-terrace house and bungalow. To simplify this analysis, and due to the negligible impact it would have on the modelling outcomes, the time that each occupant spent in the loo or bathroom was not considered.

2.2 Pollutant modelling

A whole-year simulation was run for all archetype models. The models were assumed to be located in Plymouth, an area with high geological radon levels (18), to examine the impact of monitor placement in homes where high indoor radon concentrations may be reached. The models were simulated using hourly meteorological data (including dry bulb temperature, solar data, wind speed and direction) for 2019, obtained from the Met Office MIDAS Open database (19).

For each model, $PM_{2.5}$ and radon were simulated at 5-minute timesteps, and their concentration was reported separately for each zone. Both indoor and outdoor sources were modelled for $PM_{2.5}$. A summary of assumptions for indoor generation and deposition rates is provided in Table 2. The hourly profile of outdoor $PM_{2.5}$ concentration for 2019 was sourced from the Department for Environment Food and Rural Affairs' (Defra) Data Archive (20). Radon was modelled as entering the house through the air leakage of soil gas radon from the ground using a pressure-driven model of radon entry, described in detail by Wang et al. (11). Other sources of radon entry (e.g. from outdoor air) were not considered since air leakage of soil radon gas is generally the dominant method (21). In modelling radon, we assumed the air permeance of the ground to be 10^{-3} $m^3/(m^2\ hPa)$ (21), and soil gas radon concentration to be 64 kBq/m^3 (22).

Contaminant activity	**Rate/Factor**	**Schedule**
$PM_{2.5}$ emission from cooking	1.6 mg/min	Weekdays: 7.20-7.35, 18-18.30 Weekends: 8.45-9, 12.30-13, 18-18.30
$PM_{2.5}$ deposition	-0.39/h	24 h
$PM_{2.5}$ penetration factor	0.8	Windows closed
$PM_{2.5}$ penetration factor	1.0	Windows open

Table 2 –$PM_{2.5}$ assumptions based on Shrubsole et al (23)**.**

2.3 Occupant exposure

To estimate the exposure of each occupant to $PM_{2.5}$ and radon, the following equation was used:

$$e_{p,i,t} = \sum_{r=1}^{R} o_{i,r,t} c_{p,r,t} \quad [1]$$

where:

- $c_{p,r,t}$ is the pollutant concentration for pollutant p, in room r at time t
- $o_{i,r,t}$ is an indicator variable that signifies whether individual i occupies room r at time t, taking values of 1 or 0. Since an occupant can only be in one room at time t, $\sum_{r=1}^{R} o_{i,r,t} = 1$ if the occupant is at home or $\sum_{r=1}^{R} o_{i,r,t} = 0$ otherwise.
- $e_{p,i,t}$ is the exposure of individual i to pollutant p, at time t.

The *exact pollutant exposure* for each occupant, as calculated from the full dataset of concentrations in the main rooms (kitchen, living room and bedrooms) was compared against the *approximate exposure* estimated when data on pollutant concentrations were available for only subsets of the rooms. To estimate the approximate exposure, the process described in Table 3 was followed. This process assumes that: (i) if data are only available from one room, that data offer the best indication of the occupant's pollutant exposure at home, and (ii) if data from two rooms are available, day-time data from the living room or kitchen are most representative of the occupant's exposure, while night-time data from a bedroom are preferred. Assumption (ii) depends on the assumed occupancy of individuals, and in this paper the occupants are not assumed to spend any time in their bedroom during daytime.

<table>
<tr><th>Rooms for which data are available</th><th>Process to estimate exposure</th></tr>
<tr><td>Any one room</td><td>All hours that occupants are at home are associated with data from that room, regardless of the location of the occupants in the home.</td></tr>
<tr><td rowspan="2">Living room and one bedroom</td><td>For occupants whose bedroom is being monitored:
• For hours that occupants are in the kitchen, pollutant data were taken from the living room.</td></tr>
<tr><td>For occupants whose bedroom is not monitored:
• For hours that occupants are in the kitchen, pollutant data were taken from the living room.
• For hours that occupants are in the bedroom, pollutant data were taken from the monitored bedroom.</td></tr>
<tr><td rowspan="2">Kitchen and one bedroom</td><td>For occupants whose bedroom is being monitored:
• For hours that occupants are in the living room, pollutant data were taken from the kitchen (assumed to be more representative of daytime exposure than the bedroom).</td></tr>
<tr><td>For occupants whose bedroom is not monitored:
• For hours that occupants are in the living room, pollutant data were taken from the kitchen (assumed to be more representative of daytime exposure than the bedroom).</td></tr>
</table>

	• For hours that occupants are in the bedroom, pollutant data were taken from the monitored bedroom.

Table 3 – Process to estimate approximate exposure using data from a subset of the rooms.

The approximate exposure for each archetype, occupant and pollutant was calculated for five synthetic experiments representing data being available for a subset of rooms, as summarised in Table 4. The first three experiments considered the case where only one room is being monitored, with the last two experiments looking at the effects of monitoring the main bedroom (Bedroom 1) and the kitchen or living room. This is a non-exhaustive list of room combinations, but it was considered representative of typical practices of indoor air quality monitoring (24,25).

Experiment	Living room	Kitchen	Bedroom 1	Bedroom 2	Bedroom 3
K	N	**Y**	N	N	N
L	**Y**	N	N	N	N
B1	N	N	**Y**	N	N
LB1	**Y**	N	**Y**	N	N
KB1	N	**Y**	**Y**	N	N

Table 4 – Rooms being monitored per experiment.

2.4 Comparing exposure

To compare the exposure estimated for each occupant from the full dataset against the approximate exposure, four performance metrics were used: (i) the Root Mean Square Error (RMSE), (ii) the Mean Bias Error (MBE), (iii) the Coefficient of Variation of Root Mean Square Error (CV(RMSE)), and (iv) the Normalised Mean Bias Error (NMBE).

RMSE for pollutant p and individual i is defined as (26):

$$RMSE(p,i) = \sqrt{\frac{1}{T_i}\sum_{t=1}^{T_i}\left(e_{p,i,t} - e_{p,i,t}^{(a)}\right)^2} \quad [2]$$

T_i is the total number of timesteps that individual i is at home over the year, and $e_{p,i,t}^{(a)}$ is the approximate pollutant exposure.

MBE is defined as (27):

$$MBE(p,i) = \frac{1}{T_i}\sum_{t=1}^{T_i}\left(e_{p,i,t} - e_{p,i,t}^{(a)}\right) \quad [3]$$

MBE represents the mean difference in exposures, and it is subject to cancellation errors; its sign indicates whether the model underpredicts (positive) or overpredicts (negative) compared to the monitored data.

Both RMSE and MBE return values in the same unit as the quantity being evaluated, in this case, pollutant exposure. To transform the error estimates into percentage estimates, the mean occupant exposure ($\overline{e_{p,i}}$) was considered (27):

$$CV\big(RMSE(p,i)\big) = \frac{1}{\overline{e_{p,i}}} RMSE(p,i) \times 100\ \%\,, \tag{4}$$

$$NMBE(p,i) = \frac{1}{\overline{e_{p,i}}} MBE(p,i) \times 100\ \%\,. \tag{5}$$

3. Results

RMSE, MBE, CV(RMSE) and NMBE were estimated for each pollutant, archetype and occupant. The results for $PM_{2.5}$ are presented in Section 3.1, Figures 3 and 4, and for radon in Section 3.2, Figures 5 and 6. For each figure, the y-axis and bar height correspond to the non-normalised metrics (RMSE and MBE), while the percentage-based value above or below each bar corresponds to the normalised metrics (CV(RMSE) and NMBE). It should be highlighted that the mean occupant exposure, used to normalise RMSE and MBE (Equations 4 and 5), may differ between occupants and archetypes.

3.1 $PM_{2.5}$ comparison

For adult 1, who is the occupant present in the kitchen during cooking activities, $PM_{2.5}$ data from only the kitchen (experiment K) results in the smallest RMSE amongst the experiments focused on data from just one room (Figure 3). This is the case regardless of the typology. For experiment K, RMSE ranged from 9.1 μg/m^3 in the bungalow to 21.4 μg/m^3 in the flat. In comparison, experiment L and B1 RMSE ranged between 31.8-62.2 μg/m^3 and 31.5-62.2 μg/m^3, respectively. In terms of CV(RMSE), the errors associated with experiment L or B1 ranged between 242-270%, whereas the errors associated with experiment K ranged between 56-121%. Collecting data from the kitchen and bedroom 1 (experiment KB1) reduces the RMSE for adult 1, when compared to using data only from the kitchen, but the improvement is small (0.3-0.5 μg/m^3). Looking at the tendency to under- or over-predict (Figure 4), data from only the kitchen results in overprediction for adult 1, with the MBE (NMBE) ranging from -0.5 μg/m^3 (-4%) in the bungalow to -4.4 μg/m^3 (-29%) in the mid-terraced house. On the other hand, collecting data only from the living room or bedroom 1 results in an underprediction of up to 14.4 μg/m^3 (63%; flat – living room).

For all other occupants, the effect of utilising data from only one room is reversed. Utilising data only from the kitchen results in the largest RMSE and MBE for all occupants, except adult 1, and for all typologies. As adult 2 and the children spend little time in the kitchen during cooking activities, utilising data collected in the kitchen to estimate their exposure leads to an overprediction (MBE) of up to 16.8 μg/m^3 (NMBE of 155%; flat – adult 2). Supplementing kitchen data with bedroom 1 data results in a marginal improvement of 3.6 μg/m^3 (flat – adult 2). Contrary to the case of

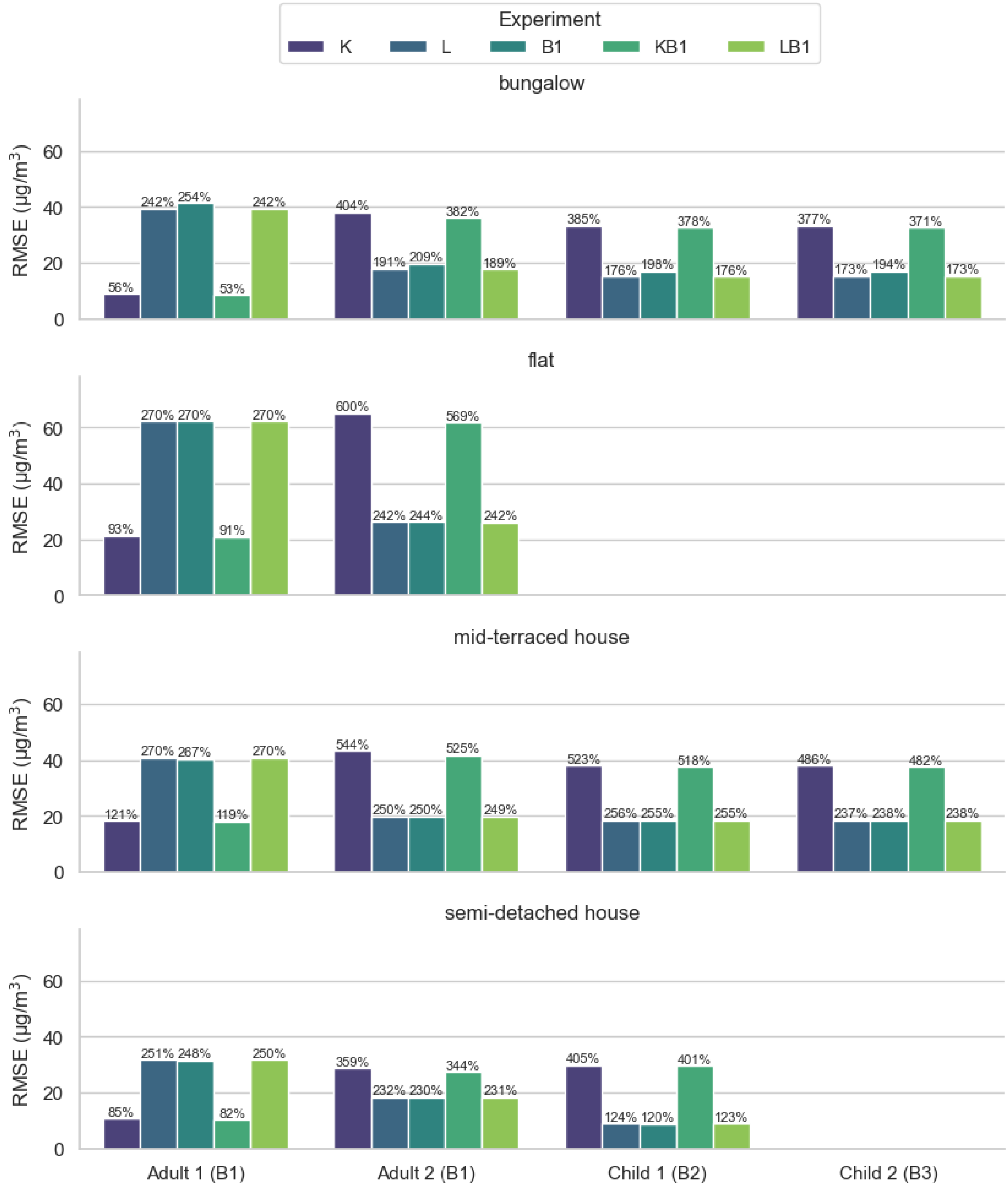

Figure 3 – Root Mean Square Error (RMSE; y-axis and bar height) and Coefficient of Variation of RMSE (percentages above each bar) of $PM_{2.5}$ exposure per occupant depending on the data being used. Each occupant's bedroom is specified next to their name.

adult 1, the use of data from only the living room or bedroom 1 results in smaller RMSE and MBE for all other occupants. The differences in RMSE between using the living room or bedroom 1 data are marginal, as is the improvement from collecting data from both rooms.

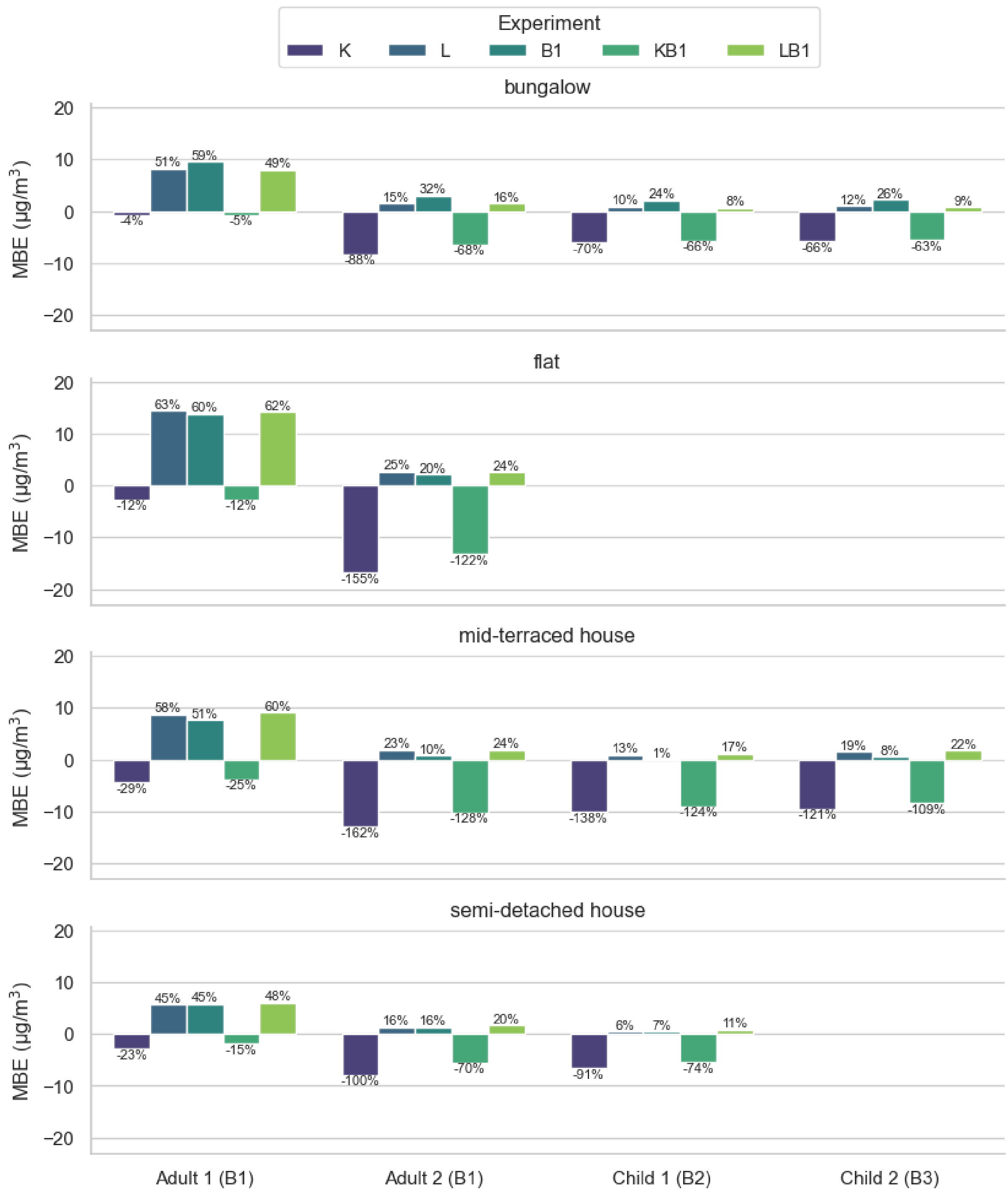

Figure 4 – Mean Bias Error (MBE; y-axis and bar height) and Normalised MBE (percentages above or below each bar) of $PM_{2.5}$ exposure per occupant depending on the data being used. Each occupant's bedroom is specified next to their name.

3.2 Radon comparison

Focusing on RMSE and CV(RMSE), the smallest errors are associated with the two adults (Figure 5). Amongst the cases where data from only one room were used (experiments K, L, B1), the use of bedroom 1 data (experiment B1) resulted in the

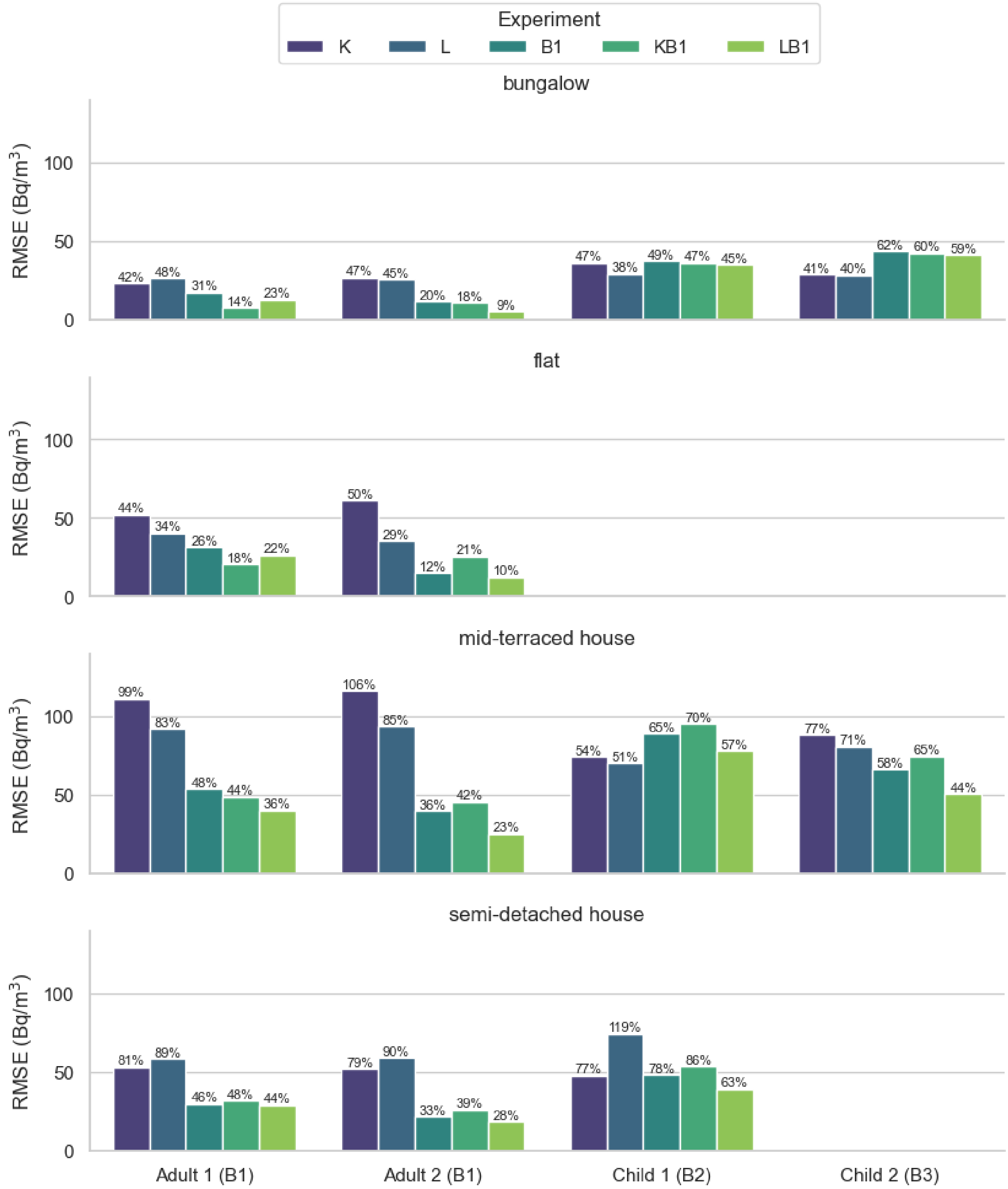

Figure 5 – Root Mean Square Error (RMSE; y-axis and bar height) and Coefficient of Variation of RMSE (percentages above each bar) of radon exposure per occupant depending on the data being used. Each occupant's bedroom is specified next to their name.

smallest RMSE for adult 1 (17.2-53.7 Bq/m^3) and 2 (11.5-39.6 Bq/m^3), regardless of the archetype. The use of data from two rooms tends to decrease the RMSE, although the changes can be small, and vary between occupants and typologies. Contrary to the case of the adults, the use of bedroom 1 data, on their own or in combination with other room data, do not consistently result in the smallest RMSE for the children. For the cases where bedroom 1 data are used (B1, KB1, LB1), the mean RMSE for the children is 55.4 Bq/m^3, 120% greater than the mean RMSE for

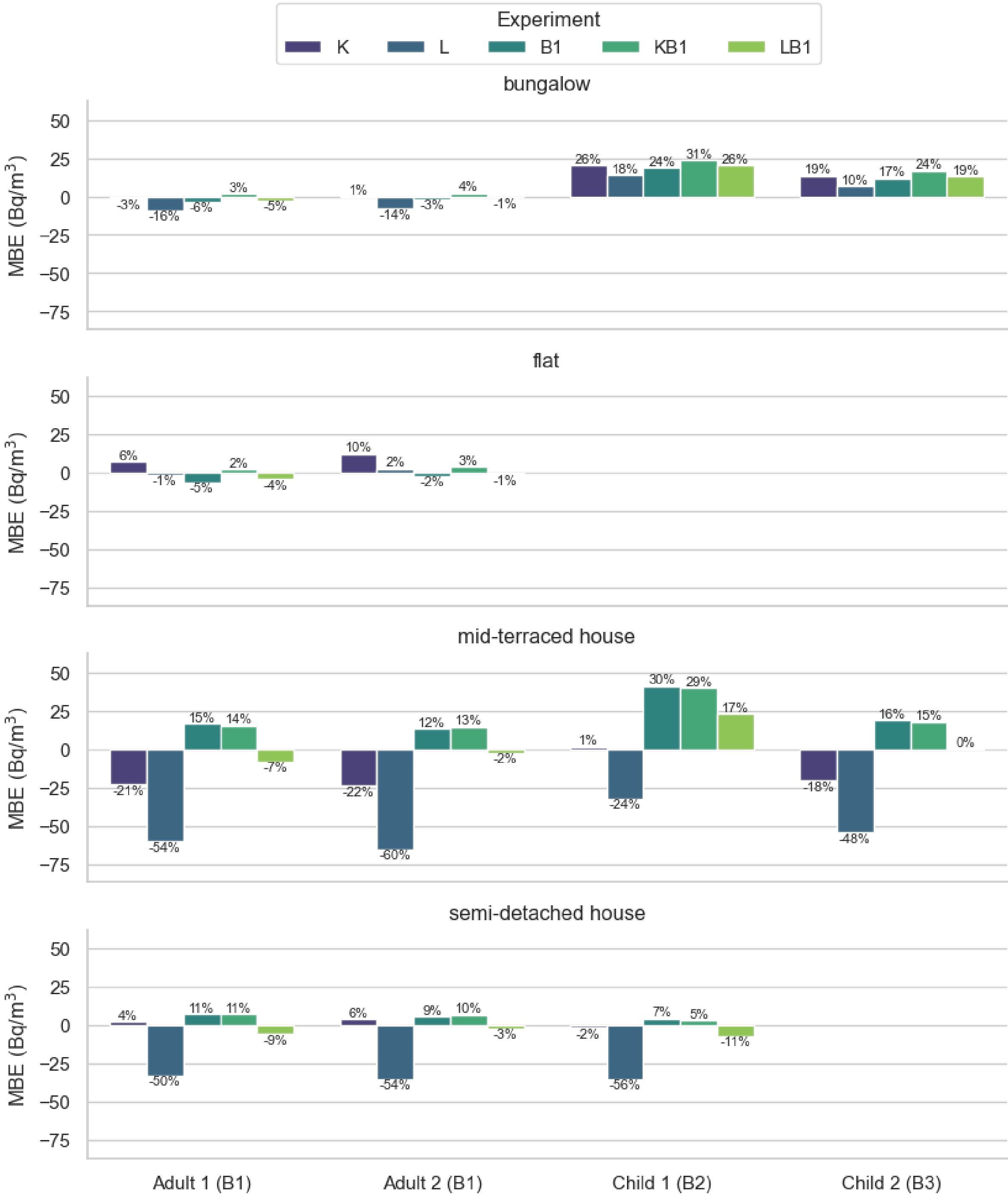

Figure 6 – Mean Bias Error (MBE; y-axis and bar height) and Normalised MBE (percentages above or below each bar) of radon exposure per occupant depending on the data being used. Each occupant's bedroom is specified next to their name.

the adults (25.2 Bq/m^3). The greatest CV(RMSE) was observed for child 1 in the semi-detached model, with a value of 119%.

Based on Figure 6, the mean discrepancy for the two adults is smaller than that of the children for most comparable cases. Looking at the bungalow, the approximate exposure for the adults can on average be smaller or greater than the exact exposure depending on the data used (MBE: -9.0-2.2 Bq/m^3; NMBE: -16.5-3.9%).

For the children, regardless of the room being monitored, the approximate exposure is smaller – on average – than the exact exposure (MBE: 6.8-23.6 Bq/m^3; NMBE: 9.8-30.7%).

Another trend that can be observed in Figure 6 relates to the mid-terraced and semi-detached; the two archetypes that have two storeys, with the living room and kitchen located on the ground floor and the bedrooms located on the first floor. For the mid-terraced and semi-detached archetypes, there is consistent overprediction (negative MBE) for all occupants when only the living room data are used (experiment L). The same effect is not observed when data are only taken from the ground floor kitchen of the mid-terraced and semi-detached house; the MBE for experiment K can be both positive or negative, depending on the case, and have a smaller magnitude to that experiment L. However, the RMSE errors of the kitchen data are comparatively high to those of the living room.

4. Discussion

Multizonal modelling of radon and $PM_{2.5}$ in four archetypical UK housing models was used to explore the potential effects that the number and location of air quality monitors has in quantifying pollutant exposure. By comparing the modelled exposure for each occupant – estimated from the complete dataset – to the approximate exposure based on subsets of the rooms, this work revealed that discrepancies exist and differ depending on the pollutant and archetype being considered, and the occupant for whom exposure was estimated.

The modelling of $PM_{2.5}$ captured the effect of indoor and outdoor sources. Indoor-sourced $PM_{2.5}$ was the result of cooking in the kitchen, leading to a substantial and localised generation of $PM_{2.5}$ at 1.6 mg/min. Utilising data from the kitchen was shown to result in the smallest errors for the occupant (adult 1) present in the kitchen during cooking. On the contrary, for occupants who spent little or no time in the kitchen during cooking, the use of kitchen data led to larger discrepancies and consistent overprediction of their $PM_{2.5}$ exposure. Pollutant exposure is a function of the time spent in different rooms, and the levels of pollutant concentration in each room during this time. Thus, collecting data from rooms with strong pollutant sources is important when estimating the exposure of occupants who spend time in such rooms when concentration levels are high. However, the use of this data alone can be misleading for occupants that spend a limited amount of time in that room when the pollutant concentration level is low.

Radon entry was modelled to be the result of pressure-driven ingress of radon gas from the ground (11). Thus, the entry of radon gas was broadly uniform across the rooms at the ground floor level of each house (except for small variations due to the indoor temperature in each room). For occupants assumed to sleep in a given bedroom, data from that bedroom resulted in the smallest errors when only one room was being monitored. The errors reduced further if the occupants' bedroom and another room was being monitored. However, utilising data from a different bedroom to the one that the occupants use for sleep can result in substantial differences, even when the bedrooms are on the same storey. This is likely due to differences in air exchange between rooms that might be the result of their physical characteristics (number of exposed walls, number of openings, orientation etc.) and differences in occupant activities.

For multi-storey houses (semi-detached and mid-terraced archetypes), the bedrooms were assumed to be on the first floor. The errors associated with the use of radon data from the bedroom (experiment B1) of multi-storey houses were larger than the errors associated with single-storey houses (bungalow and ground-floor flat), and this was true regardless of the occupant being considered. Further, the use of data from the living room (experiment L), resulted in consistent overprediction of occupant exposure. This is due to the greater accumulation of radon in the living room, since it is located on the ground floor. While the RMSE errors were comparatively large when data from the ground floor kitchen were used (experiment K) as for the living room in the two-storey archetypes, the MBE was smaller than for experiment L and could be both positive and negative. Thus, the use of kitchen data resulted in periods of underprediction, and periods of overprediction – likely due to its ventilation schedules – that largely cancelled out these differences. However, given the large RMSE of experiment K, and the fact that ventilation practices vary between dwellings, the use of radon data only from the ground-floor kitchen should not be considered a reliable proxy for occupant exposure in multi-storey houses. Data from rooms on all storeys are likely to provide a more accurate picture of occupant exposure, at least for occupants whose bedroom is being monitored.

4.1 Implications

Findings from this work have important implications for academic research and industry practice. The differences in occupant exposure observed within this study suggest that the number and placement of monitors is an important consideration, and using a limited number of monitors could result in potentially substantial discrepancies between the estimated and true indoor pollutant exposure.

In applications where measurements may be used to estimate and quantify the health impacts of exposure to different pollutants, using a limited number of sensors may introduce bias. As an example from this paper, the mean bias for one of the occupant's (child 1) of the bungalow model ranged between 13.7 Bq/m^3 and 23.6 Bq/m^3, corresponding to normalised bias (in relation to the occupant's mean annual exposure) of 18-31%. In the case of the mid-terraced model, the mean (and normalised) bias for adult 2 ranged from -2.6 Bq/m^3 (approximately -2%) to -65.6 Bq/m^3 (-60%). Reducing this bias requires the monitoring of all rooms where substantial exposure is likely to occur.

If factors such as cost prevent the comprehensive monitoring of dwellings, it is important to prioritise rooms depending on the pollutant being monitored and the typical use of each room by each occupant. Gathering data on typical use per room and by each occupant ahead of a monitoring campaign, in addition to identifying key pollutant sources, may allow for a subset of rooms to be effectively selected for monitor placement. Where the placement of monitors is not informed by the location of sources, and occupant activities, and instead an approach of monitoring the same subset of rooms regardless of the pollutant being considered, there is a risk of consistently under- and over-estimating the exposure for some occupants. This was most pronounced in this study when looking at exposure of $PM_{2.5}$ for occupants that were, or were not, present in the kitchen during cooking activities, with the normalised mean bias error ranging from -162% to 63%.

4.2 Strengths and weaknesses

While there is a growing body of research on the topic of sensor placement (9,10), to our knowledge, this is the first paper to focus on indoor exposure to $PM_{2.5}$ and radon in UK homes. We employed a state-of-the-art co-simulation method that draws on the strengths of two established building physics software, EnergyPlus and CONTAM. By examining the impact on two pollutants with different generation mechanisms, in four UK archetype models and separately for up to four occupants per model, we demonstrated that differences in building typology and occupant activities can influence the approximate estimates of pollutant exposure.

While this novel work has resulted in findings of importance to academia and the industry, it is important to reflect upon its limitations. As with any modelling approach, it is but a simplification of real life and the quantitative estimates derived from this process depend on the modelling assumptions made. However, modelling can offer useful insights in this case, and our assumptions regarding pollutant generation, occupant activities and dwelling characteristics are based on published literature and aimed to represent typical values. Nevertheless, variability in many of the key model inputs exists within the UK housing stock, and a comprehensive investigation of the effects of this variability was not pursued within this study. Thus, the findings cannot be generalised to other homes and should be considered within the context of our case study models and their assumptions. Some of our key modelling limitations include: (i) modelling outdoor levels of $PM_{2.5}$ as spatially homogeneous, (ii) considering only cooking as a source of indoor $PM_{2.5}$, (iii) considering only four occupant profiles, (iv) assuming well-mixed indoor air. Finally, while focusing on five options for sensor placement was sufficient in highlighting the impact that this choice has on monitoring occupant exposure, it was not an exhaustive study of all possible combinations.

5. Conclusions

The importance of monitoring indoor air quality in UK homes, especially as wide-scale changes to the housing stock are required to reach Net Zero, has been previously highlighted. To contribute to the effective monitoring of indoor air, a modelling approach was used to investigate the impact that monitor placement has on quantifying indoor occupant exposure to fine particulate matter ($PM_{2.5}$ – indoor- and outdoor-sourced) and radon. The approximate occupant exposure, estimated using data from only a subset of the rooms, was shown to differ from the occupant exposure estimated using the complete dataset. The differences depended on the sensor location, the occupant, pollutant and archetype being considered.

In the case of $PM_{2.5}$, where exposure was largely driven by cooking activities, collecting data only from the kitchen exaggerated the exposure for occupants that were not present during cooking. On the other hand, not monitoring such a room was shown to underestimate the exposure of someone present during cooking activities by up to 63% (normalised mean bias error - NMBE). Monitoring radon concentration in the main bedroom was revealed to be important in quantifying the radon exposure of occupants that sleep in that bedroom. However, substantial differences (NMBE: -56-30%) were observed when data from the main bedroom were used to estimate radon exposure for occupants that did not sleep in the main bedroom, even when the bedrooms were on the same storey. For multi-storey homes, collecting data from rooms on every storey would likely provide a more accurate picture of occupant exposure, at least for occupants whose bedroom is being monitored. Overall, if possible, all rooms where substantial exposure to a given pollutant should be monitored. Given that differences were shown to exist between occupants of the same modelled dwelling, generalising measurements from rooms typically occupied by some occupants to the rest of the household should be done with caution.

This work contributes directly to the body of knowledge that can be used to develop guidance on monitoring indoor air quality in UK homes. Future modelling and empirical work should seek to explore more variations of dwelling and occupant characteristics, consider more pollutants, and define best practice for different scenarios and policies.

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