Article

Improving indoor air quality and occupant health through smart control of windows and portable air purifiers in residential buildings

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Abstract

Indoor exposure to $PM_{2.5}$ (particulate matter with aerodynamic diameter less than 2.5 μm) has a substantial negative impact on people's health. However, indoor $PM_{2.5}$ can be controlled through effective ventilation and filtration. This study aimed to develop a smart control framework that (1) combines a portable home air purifier (HAP) and window control system to reduce indoor $PM_{2.5}$ concentrations whilst maintaining thermal comfort; (2) evaluates the associated health impacts and additional energy use. The proposed framework was demonstrated through a simulation-based case study of a low-energy apartment. The simulation results showed that joint control of HAP and window openings has great potential to not only maintain thermal comfort but also achieve effective $PM_{2.5}$ removal which, consequently, can lead to considerable health benefits at a low additional energy cost. Compared to similar previous studies, the strength of the proposed control framework lies in combining window operations and HAPs in the same system and including both thermal comfort and indoor $PM_{2.5}$ as the control targets. This work also introduces a novel concept of linking a building control system with a health impact assessment, an important and innovative step in the creation of holistic and responsive building controls.

Practical application: This study proposes a novel control framework that jointly controls portable home air purifiers (HAPs) and windows to maintain thermal comfort and achieve effective $PM_{2.5}$ removal. The simulation results suggest that such a hybrid control strategy can result in considerable health benefits at low additional energy costs.

Keywords

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Introduction

Considerable research efforts have been made in recent decades to improve indoor air quality (IAQ) to provide healthy indoor environments for occupants. Currently, carbon dioxide (CO_2) sensors are commonly used in building control systems,[1] but CO_2 is not representative of all indoor air pollutants including particulate matter (PM). PM refers to a mixture of airborne liquid droplets and solid particles and is categorised as PM_1 (≤ 1 μm), $PM_{2.5}$ (≤ 2.5 μm) and PM_{10} (≤ 10 μm) based on aerodynamic diameter. $PM_{2.5}$ is of particular concern because it can infiltrate deeply into the respiratory system, causing severe health problems including cardiovascular diseases and asthma.[2,3] A link has been established between exposure to $PM_{2.5}$ and an increase in all-cause mortality.[2] Thus, reductions in $PM_{2.5}$ are estimated to have major health benefits.[4]

Due to the important role window opening plays in shaping the indoor environment, implementing automatic window control systems has been deemed a promising building control strategy. Several papers reported the findings of deploying automated window systems to facilitate ventilative cooling,[5–7] or minimise the amount of time with high indoor CO_2 concentration.[8] In comparison, very limited studies of window control systems considered indoor $PM_{2.5}$. As one rare example, An et al.[9] recently used the reinforcement learning approach to develop an automatic window control system to mitigate indoor $PM_{2.5}$. However, when outdoor air quality is poor, this approach cannot reduce indoor $PM_{2.5}$ concentrations. In this regard, it is worthwhile to consider alternative strategies such as portable home air purifiers (HAPs) that use high-efficiency particulate air (HEPA) filters. Notably, the new generation of HAPs (such as those used in a recent study[10]) has built-in $PM_{2.5}$ sensors and can be connected to the internet to realise instant remote control, showing great potential to be part of an advanced building automation system.

This paper presents a novel control framework that integrates HAPs and automatic window systems to reduce indoor $PM_{2.5}$ concentrations and maintain thermal comfort. The proposed framework was demonstrated through a simulation-based case study of a modern 1-bedroom apartment in London, UK. Compared to similar previous studies, the strength of the control framework proposed lies in combining window operations and HAPs in the same system and including both thermal comfort and indoor $PM_{2.5}$ as the control targets. This work also introduces a novel concept of linking a building control system with a health impact assessment, an important and innovative step in the creation of holistic and responsive building controls.

Material and methods

Description of case study

The case study residence is a 1-bedroom flat, approximately 51 m^2, located on the ninth floor of a 13-storey residential building built in 2015. The building is sited in a busy urban area in London, UK, adjacent to two heavily trafficked roads. The Energy Performance Certificate (EPC)[11] for the flat is band B, with band A being the highest and band D being the average rating for dwellings in England and Wales. The monitored flat was located within a building equipped with decentralised mechanical ventilation and heat recovery (MVHR) without mechanical cooling in each dwelling. The operation of the MVHR system was, therefore, individually controlled by the occupants of each flat. The filtration of the MVHR system in the case study building was found to be minimal (ISO Coarse 45%) in a previous study.[10] There was a cooking extract hood available in the open plan kitchen-living room. During the semi-structured interviews, residents from the case study flat reported that they turned on the MVHR system only occasionally, although the design intent was to provide continuous background ventilation. In regards to cooking, they reported preparing simple and quick breakfasts without using the oven or cooktop, and cooked dinner about twice a week using the front burner of the cooktop with the extract hood turned on.

Temperature, relative humidity, CO_2 and $PM_{2.5}$ were measured by air quality sensors (Eltek AQ 110) in the living room of the flat and outside the building. As shown in Figure 1, the outdoor sensor was placed on the ground floor at the left façade of building A directly facing a road. The monitored flat is situated in Building B, with only the balcony side having external walls and the other boundary walls adjacent to neighbouring flats
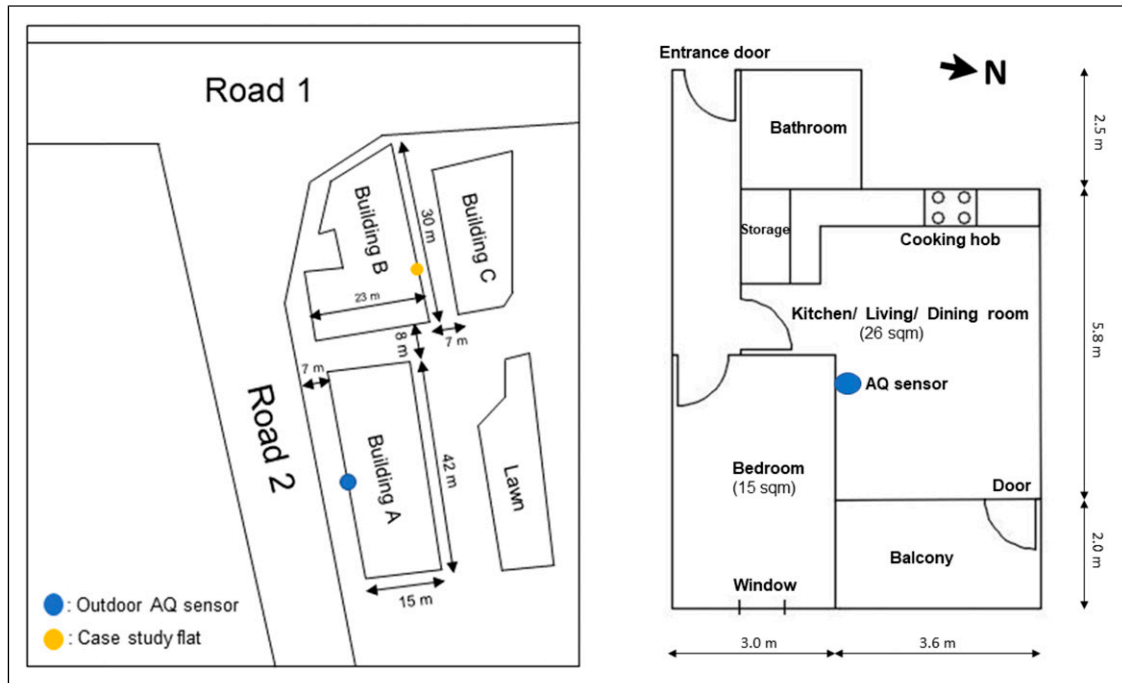
Figure 1. Indoor and outdoor monitoring locations (left) and the floor plan of the case study flat (right). Note that to protect the residents' privacy, schematic drawings were used for illustration.

or the inner corridor. The indoor sensor was placed on an internal wall of the living room (about 1.6 m above the floor), while the status (open or closed) of the double-glazed balcony door in the living room was monitored by magnetic reed switches sensors (Eltek GS34). This balcony door is referred to as 'window' in the following text. The sampling frequency for all sensors was every 5 min. The equipment specifications are detailed in Table 1. More details about the environmental monitoring and participant interviews and surveys (including sleep and wellbeing surveys, IAQ opinions, and occupant behaviours) can be found in previous publications.[10,12]

Building model development

Model inputs and assumptions. A building physics-based model was developed in EnergyPlus 9.4 (EP) to simulate indoor temperature and $PM_{2.5}$ in the living room of the flat. EP was chosen as the

simulation software because it has been previously validated in simulations of indoor pollutants and thermal environment.[13] The key input parameters and assumptions for the EP model are detailed in Table 2. The U-values for the building envelope and windows were determined in a previous case study of another flat from the same building.[14] The key parameters (e.g. discharge coefficient) related to the airflow model were estimated based on a recent calibration effort[15] focusing on the indoor CO_2 concentration of this flat. Note that because the MVHR system was rarely used, it was not considered during the EP model development phase.

Indoor $PM_{2.5}$ modelling. Cooking schedules, deposition rate and penetration factor were determined to model indoor $PM_{2.5}$ concentration. The following provides a description of the process of determination for these factors.

Table 1. The specifications of sensors.

Sensor	Parameter	Range	Resolution	Accuracy
Eltek AQ 110	Temperature	−30.0 to 65.0°C	0.1°C	±0.2°C (at 20°C)
				±0.4°C (−5 to 40°C)
				±1.0°C (−20 to 65°C)
	RH	0.0–100.0%	0.1%	±2% RH (0–90% RH)
				±4% RH (0–100% RH)
	CO_2	0–5000 ppm	1 ppm	±50 ppm
	$PM_{2.5}$ (≤2.5 μm)	0.00–500.00 μg/m^3	0.01 μg/m^3	
	PM_{10} (≤10.0 μm)			
Eltek GS34	Window status	0 (closed) or 1 (open)		

Table 2. Key inputs and assumptions for the living room in the EP model.

Category	Values/settings
External wall	U-value: 0.18 (W·m^{-2}·k^{-1})
	Air mass flow coefficient: 0.0011 (kg·s^{-1})
Window	Height: 2.0 m, width: 0.9 m
	U-value: 0.92 (W·m^{-2}·k^{-1})
	Width factor for the open state: 1
	Discharge coefficient when open: 0.65
	Air mass flow coefficient when opening is closed: 0.0001 (kg·s^{-1} m^{-1})
	Air mass flow coefficient when opening is closed: 0.0001 (kg·s^{-1} m^{-1})
	Opening schedule: Measurement data
Wall, floor, ceiling adjacent to neighbouring flats	Assumed to be adiabatic
Door to corridor	Always fully open based on occupant survey
Internal gain	Lighting: Power density (7 W/m^2) and schedule as per UK NCM[16]
	Equipment: 30% of the area as a kitchen and 70% of the area as a lounge; the power density (kitchen:30.28 W/m^2, lounge: 3.9 W/m^2) and schedules as per UK NCM[16]
Hourly external weather	Including air temperature, air relative humidity, global, diffuse and direct irradiance, wind speed and direction, obtained from London City Airport station, about 4 km away from the case study building

Emission rates (E) and cooking schedules. Smoking and cooking were previously found to be the primary sources of high indoor $PM_{2.5}$ concentrations.[17] Since the occupants of the case study flat were not smokers, only cooking was modelled here. Consistent with occupant survey results, preliminary observations of the measured indoor $PM_{2.5}$ concentrations found that there were frequent small peaks (typically around 5 μg/m^3) in the morning and occasional large peaks (usually over 50 μg/m^3) in the evening. Thus, two rules were used to generate breakfast and dinner schedules for the EP model:

1) when there was a morning peak of measured $PM_{2.5}$ concentrations of 5–10 μg/m^3 at 6–9 am, 5 min' use of microwave (E: 0.03 mg/min[18])

and toasting (E: 0.11 mg/min[18]) were assumed to occur during the corresponding period;

2) when there was an evening peak of $PM_{2.5}$ concentrations over 50 μg/m^3 at 6–9 pm, cooking (E: 1.60 mg/min[19]) was assumed to happen during the corresponding rising period, and a 20% capture efficiency (CE) of the extract hood was assumed (a midrange of the CE for the front burner that was estimated to be 4%–39%[20]).

Penetration factor (P) and deposition rate (K). From the literature, the values of both P and K are dependent on particle size. For $PM_{2.5}$, the range for the penetration factor (P) is 0.7–1.0[21]; P is less than one when the window is closed, while it should be approximately equal to one when the window is open for naturally ventilated buildings.[21,22] The measured outdoor $PM_{2.5}$ data was used as the outdoor contaminant source in the EP model. The deposition rate was reported to be more varied, e.g. 0.06–0.39 h^{-1}[22], 0.21–0.63 h^{-1}[23], 0.30–0.69 h^{-1}.[24] After comparing the simulated and measured indoor $PM_{2.5}$ concentrations, the best-fit values of P (ranging between 0.7 and 1.0) and K (ranging between 0.06 and 0.69) were found using the assumed cooking emission rate (from above), the inferred cooking schedule, and the measured outdoor $PM_{2.5}$ data.

Model tests. The outcomes of test simulations showed that the combination of K = 0.69 and p = 0.7 (when the window is closed), 1 (when the window is open) gave the best fit of the simulated $PM_{2.5}$ concentration to the measurement data, in terms of metrics listed in Table 3. Therefore, these values were adopted for all later simulation scenarios. Note that due to a lack of the heating system operational data, the model was only tested for the non-heating period.

As is shown in Figure 2, the general trends of predicted indoor $PM_{2.5}$ concentration and indoor temperature closely match the measured ones, and the large indoor $PM_{2.5}$ peaks were well captured. However, some limitations with the model were also noted. When the window was open, the estimated indoor $PM_{2.5}$ concentration could be higher than the measured indoor $PM_{2.5}$ concentration, for example, 6–9 am on 4th August. This difference was likely due to the location of the outdoor sensor which was at the ground level, directly adjacent to a busy road. The measured flat, meanwhile, was located on the other side of the building on the ninth floor (as illustrated in Figure 1). Another drawback was the disparity between the large peaks in the simulation and measured values, likely a consequence of using general assumptions about cooking emission rates and cooking schedules. Generally, the $PM_{2.5}$ model underestimates the emission rate, which leads to large errors (especially RMSE).

Control strategies and simulation scenarios

The mean of the measured indoor $PM_{2.5}$ concentrations during the monitoring period in this flat was 4.90 μg/m^3, below the WHO annual limit of 5 μg/m^3, and no days exceeded the WHO 24-h limit of 15 μg/m^3.[25] Thus, to create a case that more closely resembles $PM_{2.5}$ concentrations modelled in other intervention studies, hypothetical scenarios were developed for one summer week and one winter week. The modelled parameters are illustrated in Table 4, and represent scenarios with both high indoor and outdoor $PM_{2.5}$ concentrations. A 15-min breakfast and a 30-min dinner were set to repeat every day, based upon the cooking schedule adopted in a previous study.[19] The outdoor $PM_{2.5}$ data was sourced from an outdoor air quality station about 2.2 km away from the case study building. The chosen weeks saw higher-than-average levels of outdoor $PM_{2.5}$ concentrations in both the summer and winter periods. All control strategies were simulated using EP runtime language.

The four scenarios simulated for the summer week are described below and summarised in Table 5:

Baseline. The window is operated as measured using sensors and no HAP is used.

HAP mode. The HAP is modelled as being located in the centre of the living room, close to the occupants' seating area. The control logic illustrated in Figure 3 operates the window as measured, while the HAP is

Table 3. Comparison between simulated and measured indoor PM$_{2.5}$ concentration and indoor temperature.

Metrics	Indoor PM$_{2.5}$ concentration[a]	Indoor temperature[b]
Mean bias error (MBA)	0.68 ($\mu g/m^3$)	0.6 (°C)
Mean absolute error (MAE)	1.81 ($\mu g/m^3$)	1.2 (°C)
Root mean square error (RMSE)	5.23 ($\mu g/m^3$)	1.5 (°C)
Pearson's correlation coefficient	0.65	0.70

[a]half-hourly running means of simulated and measured indoor PM$_{2.5}$ concentrations were compared.
[b]half-hourly running means of simulated indoor air temperatures and measured indoor temperatures were compared.
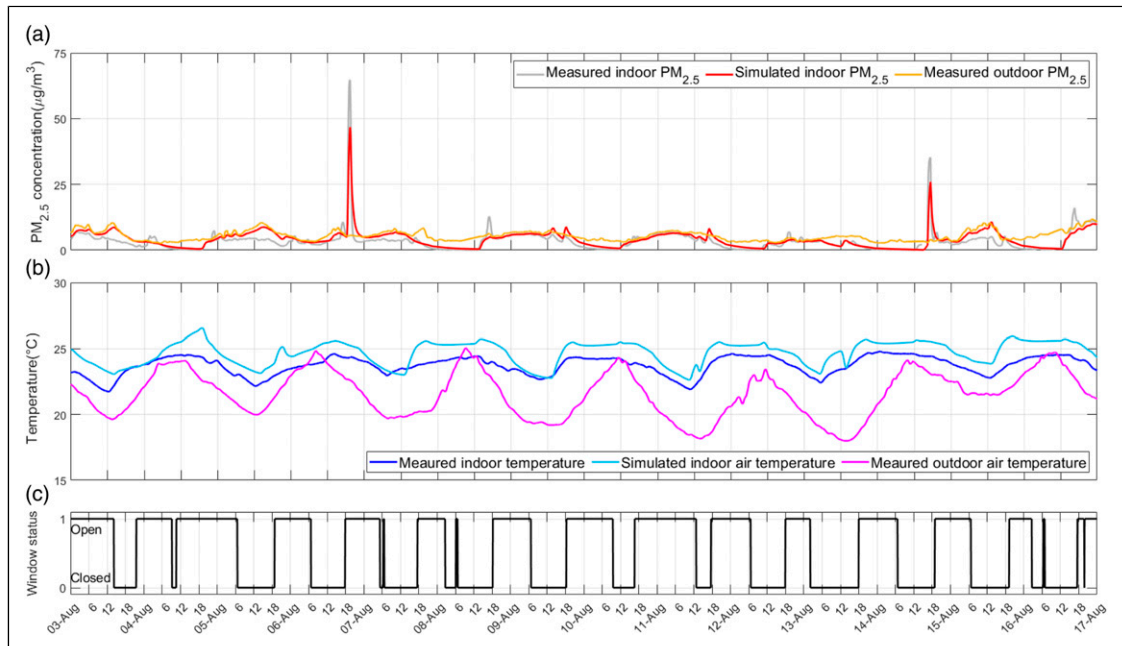

Figure 2. Demonstration of EP model estimates compared with measurements for two weeks. Note that the half-hourly running means for both PM$_{2.5}$ concentration and temperature were used to better illustrate the trend.

Table 4. Simulation setting for hypothetic summer and winter week.

Period	Dates	Cooking schedules	Outdoor PM$_{2.5}$ file
Summer week	22nd–29 August 2019	Emission rate: 1.6 (mg/min)[19]	
		Weekdays: Breakfast (7–7.15 am) and dinner (7.30–8 pm)	Sourced from Greenwich-John Harrison May station of London air quality Network https://www.londonair.org.uk/LondonAir/
Winter week	18th–25th November 2019	Weekends: Breakfast (9–9.15 am) and dinner (7.30–8 pm)	

Table 5. Controls of windows and HAPs in different scenarios.

Period	Scenario	Window operation	HAP operation
Summer week	Baseline	As measured	—
	HAP mode	As measured	Control logic in Figure 3
	Auto-window mode	Control logic in Figure 4	—
	Hybrid mode	Control logic in Figure 4	Control logic in Figure 3
Winter week	Baseline	As measured	—
	HAP mode	As measured	Control logic in Figure 3
	MVHR mode	Closed	—
	Hybrid mode	Closed	Control logic in Figure 3
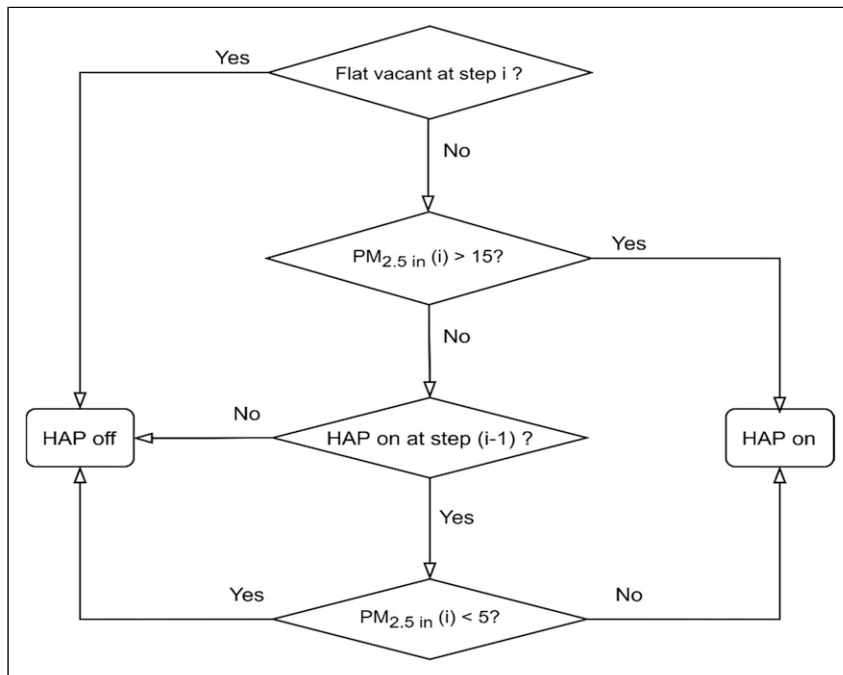
Figure 3. HAP control logic.

activated once the indoor $PM_{2.5}$ concentration reaches the 'HAP-on' threshold and stops running once the concentration falls to the 'HAP-off' threshold. The HAP-on threshold was set to be 15 μg/m³ (the WHO 24-h limit[26]) in both HAP and hybrid modes, as daily performance is of interest for this study. The HAP-off threshold was set to 5 μg/m³ in both the HAP and hybrid modes, as preliminary tests found higher HAP-off thresholds could result in cycling on/off too often. The clean air delivery rate (CADR) was

set to 303 m³/h, corresponding to a medium fan speed of the HAP with five different operating modes used in a previous study.[10] The power of the HAP was modelled as 17 W per 100 m³/h of CADR.[27] The HAP operation was assumed to be independent of the window operations based on the findings of recent work.[12,28]

Auto-window control mode. Due to security considerations, the window is programmed to be fully

closed at midnight and when people are away, and the flat-level occupancy was determined based on both passive infrared (PIR) and CO_2 sensors, with details available in a previous paper.[28] In brief, this method relied upon positive values from the PIR sensors and then used the CO_2 concentration to evaluate the negative detection results from the PIR sensors. At other times, the window is set to be fully open when the indoor temperature is above the upper limit or closed when below the lower limit of EN 16798-1 Category II adaptive comfort temperature.[29] In all other conditions, the default window setting is fully open. The control logic for the auto-window mode is illustrated in Figure 4.

Hybrid control mode. In this mode, the HAP (control logic shown in Figure 3) and window (control logic shown in Figure 4) control functions are running in
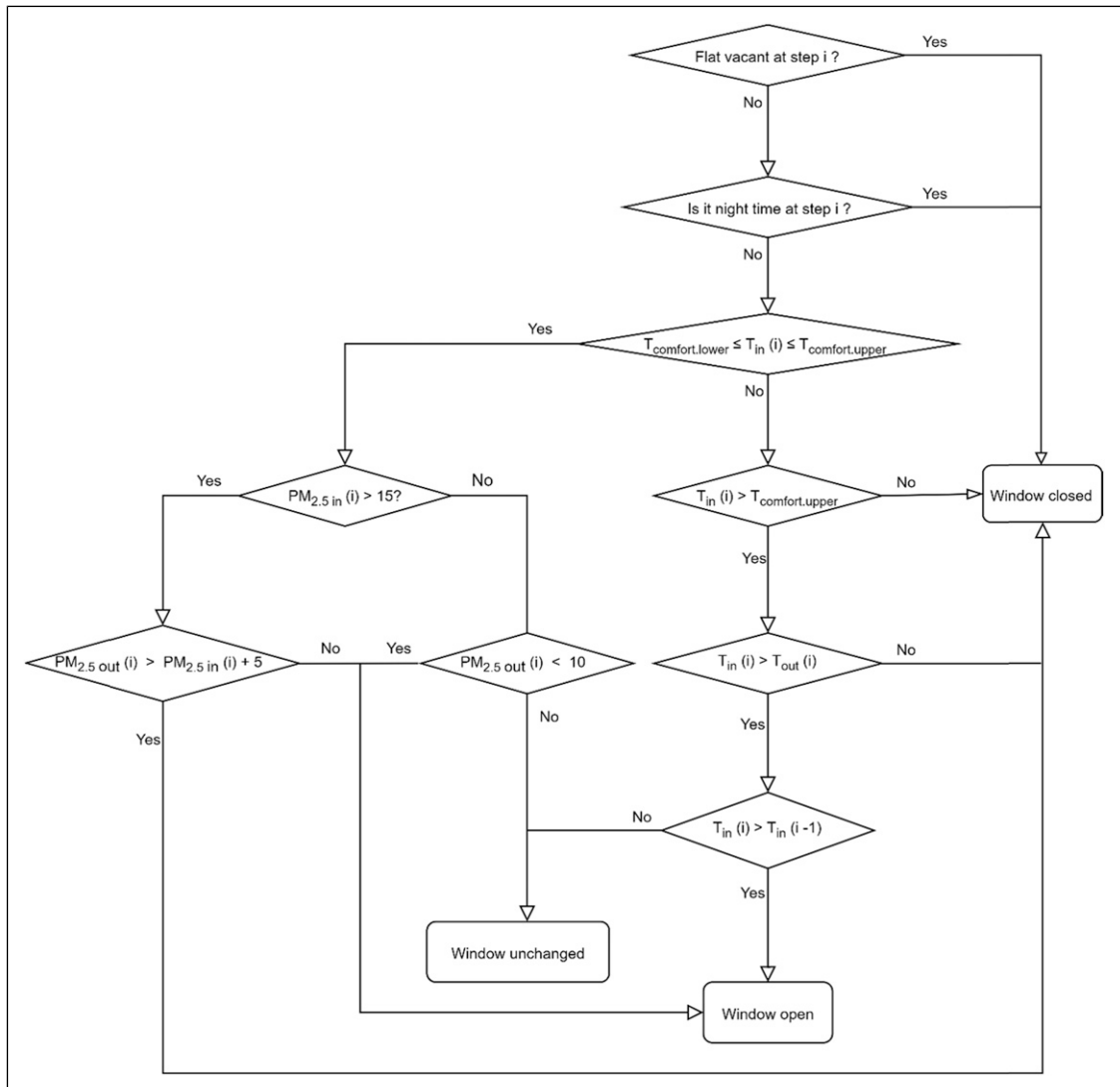

Figure 4. Auto-window control algorithm.

parallel. The window is operated to prioritise thermal comfort, as in the auto-window mode. However, if outdoor $PM_{2.5}$ concentration is high, and indoor temperature remains within the comfort zone, the window will be closed and the HAP will be running. This strategy aids in efficient HAP operation. The HAP was located and operated as described in the HAP mode.

Another set of four scenarios was also simulated for the winter week, as detailed in Table 5. The heating system was set to work with a setpoint temperature of 21°C with schedules as found in the UK NCM database.[16] No automatic window mode was modelled in the wintertime, as opening the window to reduce $PM_{2.5}$ concentration in winter would introduce a cold draught and increase the heating load. Instead, in MVHR and hybrid modes, the mechanical ventilation was simulated to provide continuous background ventilation that met the minimum requirement by the UK government (0.3 l/s/m² based on *Approved Document F Volume 1: Dwellings* 2021 edition – for use in England[30]) with the window shut to avoid heat loss. The hybrid mode for the winter week was a combination of the MVHR system and HAP. The power of the MVHR system was modelled as 42 W based on manufacturer information. No filters were modelled for the MVHR system due to the minimal filtration of the MVHR system as mentioned above.

Health impact assessment

Background and health model description. Quantitative health impact assessments are used to estimate future rates of mortality and morbidity from different interventions compared to what is predicted without such changes. These assessments were used to evaluate the impact of changes to ambient air quality at the urban and regional scales.[31] One approach to the assessment of changes in population mortality is life-table models which predict survival patterns based on changes in age-specific death rates.[32] This type of quantification of health impact has been used to assess air pollution at national scales,[33] as well as the evaluation of building-level changes in exposure.[34,35]

In the work presented here, life-table models were used to quantify the impacts on mortality from reductions in indoor $PM_{2.5}$ concentrations. Formulae from Miller and Hurley were the basis for the calculation of changes in mortality and life expectancy.[32,36] The life-table model was implemented with the open-source statistical software R.[37] A schematic diagram of the model inputs, structure and flow is presented in Figure 5. The same underlying birth and mortality rates from the starting year (2019) were assumed to apply in all future years.

Health model parameterisation. The life-table model was used to determine the benefit from the reduction of indoor $PM_{2.5}$ in residences such as the case study flat in the UK from the use of building environmental controls that automate the use of HAPs and window operations. Reductions in mean daily exposure were from the time spent in the living room where the air purifier was located and was estimated to be 7 h per day based on occupancy monitoring and other surveys.[38] The results from the modelled case study flat were used for all scenarios: the average of the modelled concentrations of the summer and winter weeks from the baseline, automated window mode in summer with MVHR system mode in winter, HAP and hybrid modes in both summer and winter.

Population and age-specific disease and mortality data for 2019 from the Office for National Statistics were used to parameterise the model. Mortality rates and relative risks (RR) for causes the Global Burden of Disease (GBD) found to be associated with $PM_{2.5}$ were included in the model: all-cause, lung cancer, chronic obstructive pulmonary disease (COPD), lower respiratory infection (LRI), stroke and ischemic heart disease (IHD). Age-specific all-cause and disease-specific mortality rates were taken from the 2019 GBD study. The upper and lower limits of the 95% confidence intervals of the RRs were calculated and used to test impacts across the range of potential risks (which will be further discussed in the next section).

Previous findings from other research showed that the use of a lag between the intervention that reduces $PM_{2.5}$ concentrations and changes in health outcomes (i.e. cessation lag) made relatively little difference to the life-table results over the long-term.[33] Therefore, the model used in the work described here does not include a cessation lag.
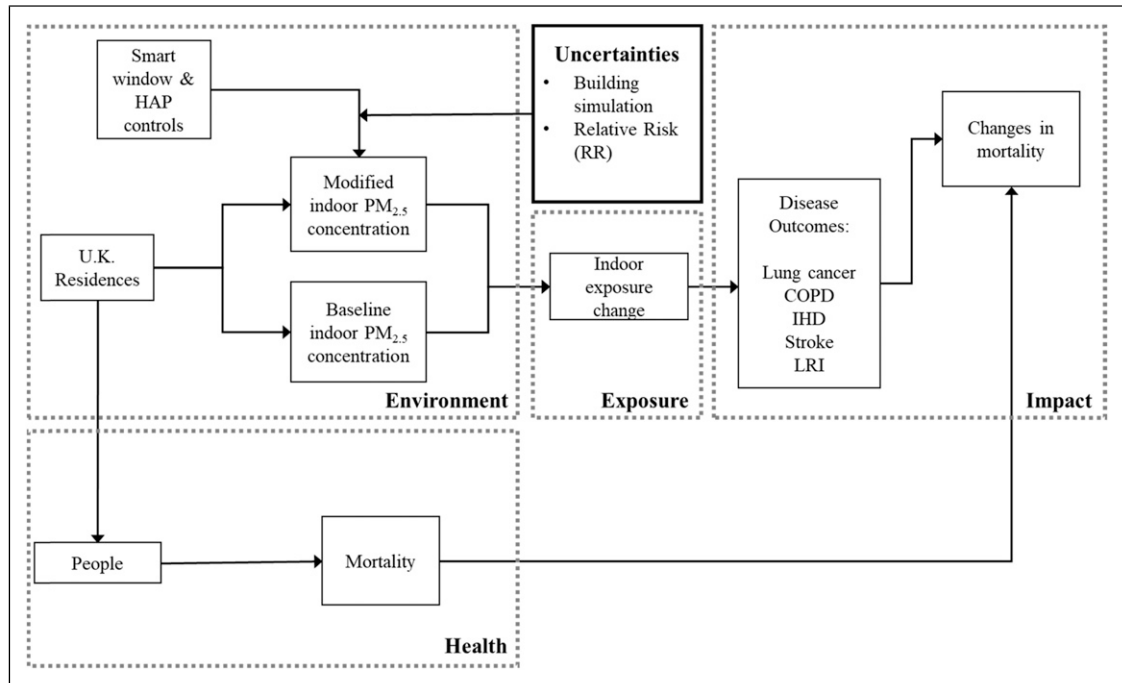
Figure 5. The conceptual framework for life-table calculations of the impact on mortality from automated control of window operations and HAP use.

Health model uncertainty analysis. Recognising that the exposure-response function per change in $PM_{2.5}$ could introduce uncertainty into the model, the effect of using the range of values within the 95% confidence intervals of the RRs derived from the 2019 Global Burden of Diseases was tested using the 95% confidence intervals. This method was in line with the recommendations for sensitivity analysis made by COMEAP.[33]

Results

Summer week

Baseline scenario. As seen in Figure 6, the daily mean of $PM_{2.5}$ concentration exceeds the WHO 24-h limit of 15 µg/m^3 on 6 days out of the week, while the indoor temperature stayed within the comfort range the whole time.

Auto-window mode. As shown in Figure 7, the automatic window system reduced the number of days

when indoor $PM_{2.5}$ concentration exceeded the WHO limit to 4 days (compared to 6 days in the baseline scenario), while still maintaining thermal comfort. The key action taken that reduced indoor $PM_{2.5}$ was the automatic opening of the window during morning cooking on the first two days. Nevertheless, the result shows that relying solely on window controls may not be sufficient when both indoor and outdoor pollution are high.

HAP mode. Note that the window opening schedule and temperature profiles for the HAP mode were the same as in the baseline scenario of the summer week. As shown in Figure 8, there were still two days (25th and 27th August) when, even with the use of HAP, the daily mean concentration of indoor $PM_{2.5}$ was above the WHO limit, with another two days (24th and 26th August) approaching the limit. The primary factor was that outdoor $PM_{2.5}$ levels were high on those days, therefore, leaving the window open for long periods worsened indoor conditions.
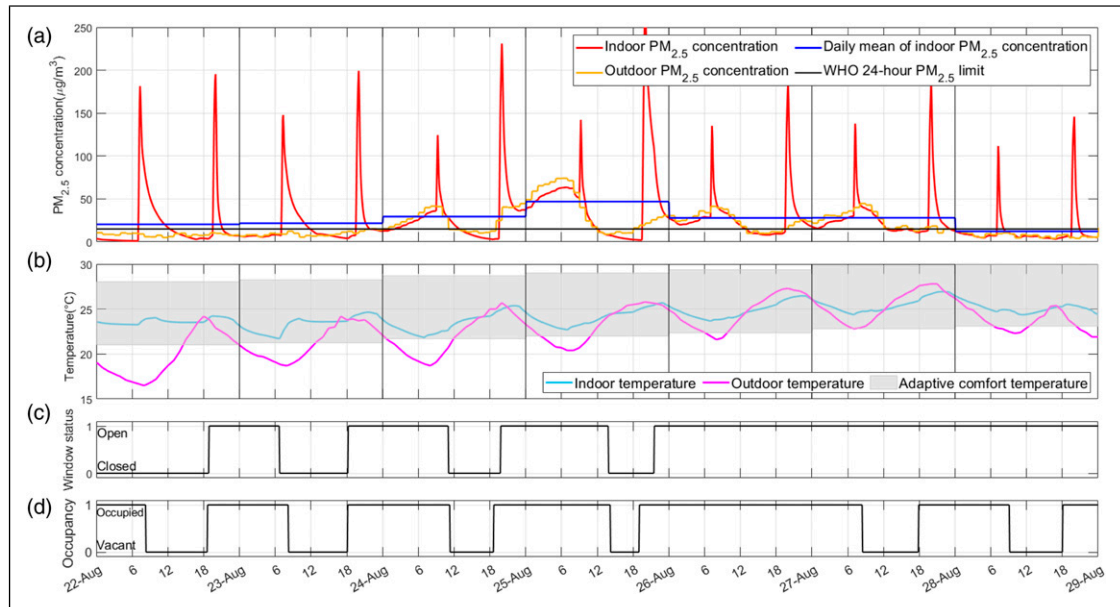
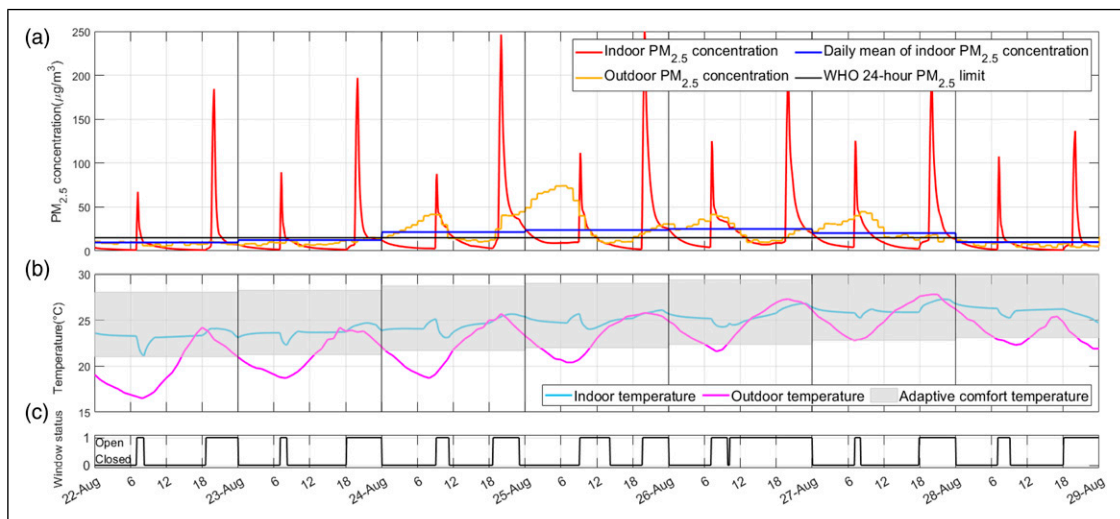**Figure 6.** Summer week: Baseline.

Figure 7. Summer week: Auto-window mode.

Hybrid mode. When both automatic HAP and window controls were used, the indoor $PM_{2.5}$ concentration was reduced substantially with no days exceeding the WHO limit. As shown in Figure 9, the indoor temperature was not compromised and stayed within the comfort range. The main advantage of the joint control of HAP and windows was that the window was shut when outdoor pollution was high,
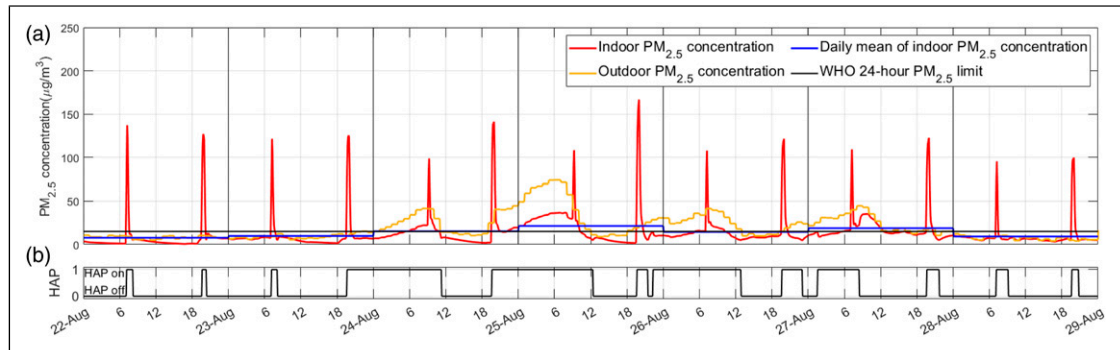
Figure 8. Summer week: HAP mode. Note that the corresponding window status and temperature profiles were the same as the baseline and are therefore not repeated here.
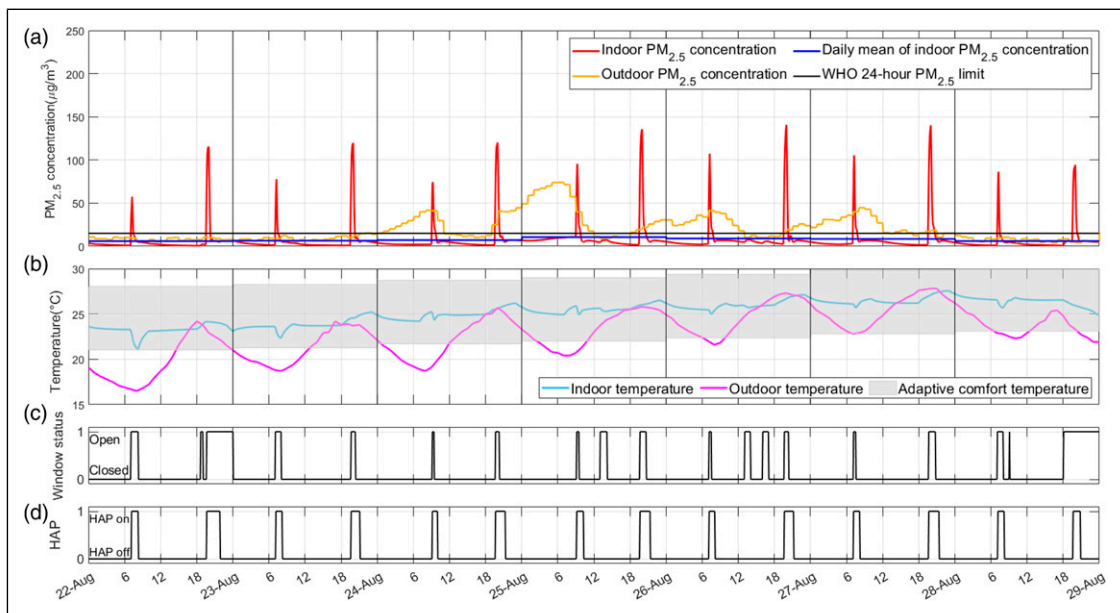

Figure 9. Summer week: Hybrid mode.

such that not only the working burden of HAP was minimised but also the overall indoor $PM_{2.5}$ concentration was lower. On the other hand, the hybrid control algorithm sought opportunities to open the window for ventilation whenever the outdoor conditions allowed. For example, on 26th August, the window was directed to be closed for most of the time, because the outdoor $PM_{2.5}$ concentration was above the defined limit, but the window was still open for a short period for three times in the afternoon and evening.

Metrics from several aspects are provided in Table 6 for each scenario in the summer week. Indoor temperature is consistently maintained within the

comfort range in each scenario. As for $PM_{2.5}$, the hybrid mode was the most effective, and noticeably, required much less electricity use than the HAP mode.

Winter week

Baseline. As shown in Figure 10, with the window mainly staying closed and the same cooking schedule, the daily mean concentration of indoor $PM_{2.5}$ was very similar across the week, almost twice

as high as the WHO 24-h limit. The indoor temperature was maintained around the heating point during the scheduled hours due to fixed heating schedules.

Mechanical ventilation and heat recovery mode. A small decrease in indoor $PM_{2.5}$ concentration was predicted to be achieved when the MVHR system was operating to provide the minimum required ventilation rate without high-grade filters, and the window staying closed, as shown in Table 7.

Table 6. Metrics for evaluation of different control modes in the summer week.

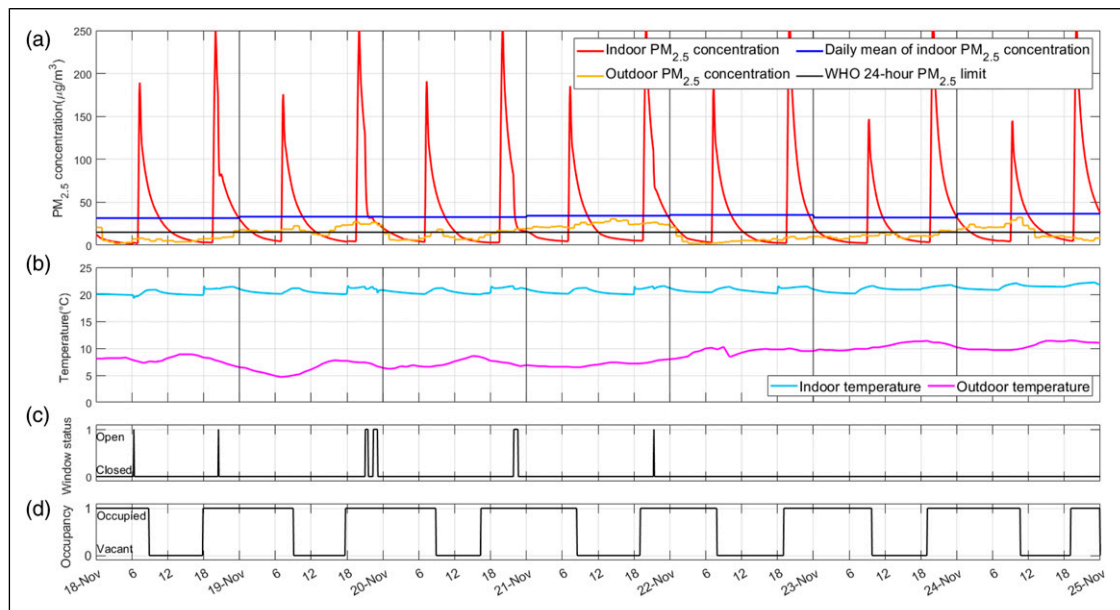|	Baseline	Auto-window mode	HAP mode	Hybrid mode
Mean indoor $PM_{2.5}$ concentration ($\mu g/m^3$)	26.64	17.45	13.80	7.67
HAP running time (hours)	—	—	67.3	19.3
Weekly HAP electricity use (kWh)	—	—	3.4	1.0
Number of days with the daily $PM_{2.5}$ concentration mean over WHO 24-h limit	6	4	2	0
Percentage of time outside comfort temperature range	0%	0%	0%	0%

Figure 10. Winter week: Baseline.

HAP mode. Utilising the HAP led to a large reduction of the indoor $PM_{2.5}$ concentration. As shown in Figure 11, the daily mean indoor $PM_{2.5}$ concentration was estimated to be below the WHO threshold on all days.

Hybrid mode. Same as in the HAP mode scenario, the purification effect was estimated to be substantial, as reflected in reduced indoor $PM_{2.5}$ levels and all daily means below the WHO limit, as shown in Table 7.

Using an MVHR system without high-grade filters was not effective in reducing indoor $PM_{2.5}$ concentration in the simulated winter scenario. The performances of HAP and hybrid modes were similar

in terms of mean indoor $PM_{2.5}$ concentration. That is because the outdoor $PM_{2.5}$ concentration was often higher than the HAP-on threshold in the studied winter week.

Health assessment

Based on the modelled indoor $PM_{2.5}$ concentrations of the case study flat, the mean years of life gained (YLGs) per 100,000 people in a population across the modelled period (97 years) was approximately 19,000, 43,000, and 51,000 for the automatic window/MVHR, HAP, and hybrid modes respectively. The results for the lower and upper confidence intervals of the relative risks, as well as the means, are shown in Table 8.

Table 7. Metrics for evaluation of different control modes in the winter week.

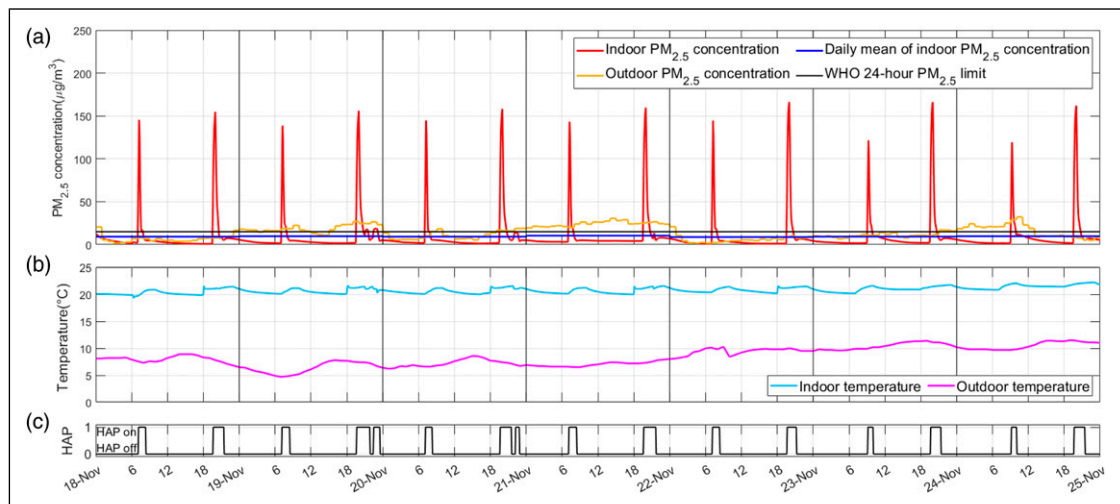|	Baseline	MVHR mode	HAP mode	Hybrid mode
Mean concentration of indoor $PM_{2.5}$ (µg/m^3)	33.67	25.75	9.54	9.82
Weekly HAP running time (hours)	—	—	23.2	21.1
Weekly HAP electricity use (kWh)	—	—	1.2	1.1
Weekly MVHR electricity use (kWh)	—	4.7	–	4.7
Number of days with the daily mean over WHO 24-h limit	7	7	0	0

Figure 11. Winter week: HAP mode.

Table 8. Summary of life-table model estimates of changes in mortality per 100,000 population from different environmental control strategies based on modelled $PM_{2.5}$ concentrations in case study flat.

Mode	Total YLG per 100,000 pop. (Mean RR)	Total YLG per 100,000 pop. (Lower limit RR)	Total YLG per 100,000 pop. (Upper limit RR)
Auto-window	18,723	13,902	23,331
HAP	43,338	30,695	56,505
Hybrid	51,094	34,561	67,965

Discussion

Strengths

The study presented here proposes a novel framework that controls both HAP operation and window opening to reduce indoor $PM_{2.5}$ concentration without compromising occupant thermal comfort. It should be noted that the presented work focuses on proposing and testing a building control framework rather than quantification of the accuracy of the simulation results. Considering that the vast majority of prior studies focused on thermal comfort and very few considered indoor $PM_{2.5}$, this work advances research on smart window control systems. Moreover, this framework aims to assess the potential health impacts associated with the adoption of building controls that reduce indoor $PM_{2.5}$ levels in homes. As reduced exposures to $PM_{2.5}$ are expected to contribute to improving occupants' health, an evaluation of intervention measures from the perspective of health benefits is meaningful but remains a missing part of previous work of the same nature.

Limitations and future work

The current building model only considered cooking as the indoor $PM_{2.5}$ source alongside a general assumption about the emission rate and cooking schedules. This simplification may not be able to estimate levels and patterns in more complicated situations, e.g. homes with smokers, occupants with more diverse cooking types (associated with a wide range of $PM_{2.5}$ emission rates) and more flexible or unpredictable cooking times. This work also did not model the range of utilisation rates or efficiencies of

cooker extract hoods reported in other studies, [20,39] although it could be a useful exploration in future research. Additionally, the proposed control framework accompanied by health impact assessments was tested in a case study flat as proof of concept, but it is expected to be more meaningful to extend this work to large-scale building stock modelling, as the life-table health modelling is a population-based method. Moreover, this proposed framework that features HAPs currently only considers $PM_{2.5}$ as the control target, but other types of pollutants such as NO_2 should be considered in future work.

The work presented here assumes that appropriate safety and protection measures (such as pinch protection and finger guards) for automatic windows can be accommodated in residential applications. Convenience, safety and security issues, and how they affect acceptance and compliance of automated systems, should be considered in future work. The model demonstrated in this work only considered fully open or closed window states due to the binary nature of the window sensor data, but future work could explore options of incremental openings. It should be acknowledged that the health impact assessment is a population-based average. The availability of data on specific indoor concentrations, health effects of reductions in indoor $PM_{2.5}$, and differences in the relative risk due to the primary source (indoor or outdoor) of PM exposure are limited. Another limitation is the relative risks used in the evaluation were drawn from the GBD[40] which were derived for ambient and household (i.e. solid-fuel combustion indoors) $PM_{2.5}$ exposures. However, previous studies have used the GBD data for the estimation of risk, and still other research has

highlighted the importance of indoor $PM_{2.5}$ to total exposure.[41–43]

Health modelling provides a useful method of evaluating the impact of interventions on population health. However, the reliability of the results is subject to the accuracy of available sources of information, and the ability to add scientific credibility when those sources are uncertain. Building simulations can allow for the provision of a rich and readily customisable dataset to add to the predictive power of health modelling when empiric data are not available. Greater integration of the building simulation to modelled health outcomes could help inform future iterations of the control framework. Additionally, as more information is gained about user behaviour and the feasibility of long-term use of HAPs, more robust estimations of actual risk reductions can be incorporated into the health impact assessments. Lastly, the model presented here does not consider morbidities, such as asthma, which are associated with $PM_{2.5}$. Future work would include a fuller range of health outcomes beyond mortality.

Conclusion

This study develops a novel control framework that integrates portable home air purifiers and window control systems with the aim to reduce indoor $PM_{2.5}$ concentrations whilst maintaining thermal comfort. The proposed framework was demonstrated through a series of building simulations for an apartment as the virtual testbed. The results show that the joint control of HAP and window operation based on indoor and outdoor environmental conditions is one control mechanism that has the potential to not only maintain thermal comfort but also achieve effective $PM_{2.5}$ removal which, consequently, can lead to considerable health benefits at a relatively low extra energy cost. The impact on population health via the implementation of the type of control logic demonstrated in this work is predicted to be substantial. The work presented here is the first known of its kind to integrate the assessment of potential changes to mortality from the implementation of advanced building control systems that measure and predict $PM_{2.5}$ concentrations indoors.

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