Uncertainty of IAQ and energy performance schemes for residential smart ventilation

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ABSTRACT

In high-efficient residential buildings, energy use due to ventilation can reach 60% of the total building. Smart-ventilation systems with variable airflows adapting to the need of buildings and occupants can increase the energy performance of the building and at the same time improve or maintain IAQ. They are also considered as a huge opportunity for new and existing residential buildings.

In some countries (like France and Belgium), smart ventilation has been widely used for dozen of years and has become reference strategies. In some other countries, smart ventilation strategies are quite recent or only partially implanted (only in some countries like Belgium, France, The Netherlands, Ireland, Spain…). Their IAQ and energy benefits need to be quantified through performance assessment schemes, still under development, notably in the framework of the IEA-EBC Annex 86. In this article, we propose to quantify the uncertainty of a new recent performance assessment method using RBD-FAST sensitivity analysis. We quantified the variations of impacts of input data such as: the pollutant emissions scenarios - moisture, formaldehyde and particle matter $PM_{2.5}$ -, model input parameters and ventilation strategies.

For this sensitivity analysis, five ventilation systems were studied on a French low energy house: 2 with constant airflows, 1 humidity-based exhaust-only smart ventilation and 2 humidity+CO_2 based smart ventilation. The sensitivity indices analysis shows that occupant bio-effluent, formaldehyde and $PM_{2.5}$ emissions rates are responsible for 11% to 87% of the uncertainty for the IAQ performance indicators. The $PM_{2.5}$ deposition velocity parameter is responsible of 50% of the uncertainty on the $PM_{2.5}$ indicator, which was an unknown impact until now and pushes toward more research in order to better characterize this parameter. In addition, the article highlights the energy benefits of this humidity-based ventilation, with heat losses on average 20% lower than those obtained with equivalent constant airflow ventilation. In addition, some smart ventilation strategies offer clear IAQ benefits without significantly increasing energy demand.

KEYWORDS

Please provide a maximum of five keywords which reflect the content of the paper

1 INTRODUCTION

Indoor environments, where people spend 60 to 90% of their time (offices, schools, homes, etc.), generally have a lower indoor air quality (IAQ) than outdoor air. In buildings, once the sources of pollutants have been reduced, ventilation systems can help to dilute pollution by renewing the air and ensuring a good level of IAQ. On the other hand, ventilation systems are also a source of heat loss due to air renewal, representing in some cases a significant percentage of the building's total energy consumption.(30%, or more according to Jardinier et al., 2018). With the advent of smart ventilation systems with variable airflow strategies, there is a need for a robust method to evaluate their IAQ and energy performance. Evaluating ventilation performance is essential to understanding the benefits of these new variable airflow strategies over historical constant airflow strategies.

A recently developed performance-based method provides an initial opportunity to assess IAQ performance for different ventilation systems and strategies, such as exhaust ventilation, balanced ventilation and humidity demand controlled ventilation (Poirier et al., 2021b). This method proposes five IAQ performance indicators (CO2, $PM_{2.5}$, HCHO, humidity, health and condensation risk) calculated using the CONTAM airflows model and input scenarios defined for occupant activities, pollutant scenarios, emissions, etc. (Poirier et al., 2021a).

However, the ventilation system performance results obtained may fluctuate depending on the input data used, and these fluctuations must be characterised. Indeed, the choice of input parameters in the building modelling process is a source of uncertainty. In the literature, several studies on building performance assessment have applied sensitivity analysis (SA) methods to test the impact of input data on output data. Such as the following non-exhaustive examples: type of architecture, air leakage, $PM_{2.5}$ deposition rate; emission rate; impact of meteorological conditions on $PM_{2.5}$ exposure, ventilation rate and heat loss. (Molina et al., 2021); the mass flow rate of domestic hot water, the air renewal rate and the occupancy schedule for the impact on hot water production with solar thermal system. (Burhenne et al., 2022); the position of shading devices controlled by the occupants, the thermal load of electrical equipment, the impact on thermal resistance and thermal stress in low-energy housing.(Gondian et al., 2019).

In this context and based on previous studies (Poirier et al., 2022a, 2022b, 2021a), we have identified several groups of input data likely to influence the proposed ventilation performance evaluation method. The main objective of this paper is to present the results of a study that quantifies the impact of input data variability on output data (performance indicators) by performing a sensitivity analysis.

2 METHODOLOGY

According to Tian's detailed review (Tian, 2013) on sensitivity analysis for building energy analysis, several methods exist and some are more relevant for building simulations. To explore the wide input space between pollutant emission scenarios, envelope air leakage, ventilation strategies and modelling assumptions, we have opted for a global method. Several methods exist, such as the mainly used Morris method, which gives a qualitative ranking of the most influential input data on the selected output, or variance-based methods, such as the ANOVA (analysis of variance) approach, which calculates the Sobol first-order sensitivity index, or ANOVA-FAST, which gives the variance of all input data on the output.(Mechri et al., 2010; Tian, 2013).

However a more recent method, EASI RBD-FAST (Goffart et al., 2015; Plischke, 2010) adapted from a combination of random balance design (RBD) (Tarantola et al., 2006) and Fourier amplitude sensitivity (FAST) (Saltelli and Bolado, 1998; Mara, 2009) seemed well suited to our objectives. Goffart's (Goffart and Woloszyn, 2021) work on sensitivity analysis demonstrated that the RBD-FAST method was more appropriate for building simulation and performance evaluation than the Morris method. The EASI RBD-FAST method can be applied independently of the model and its complexity, and provides more information than the Morris method, such as quantified sensitivity indices and an analysis of the uncertainty in the inputs and outputs. It also has a lower computational cost than conventional variance-based methods and can easily be used to build simulations using SALib, a sensitivity analysis toolkit in Python (Herman and Usher, 2017; Iwanaga et al., 2022).

Based on the key steps for sensitivity analysis in building performance analysis presented in (Tian, 2013), we designed the methodology presented in Figure 1.

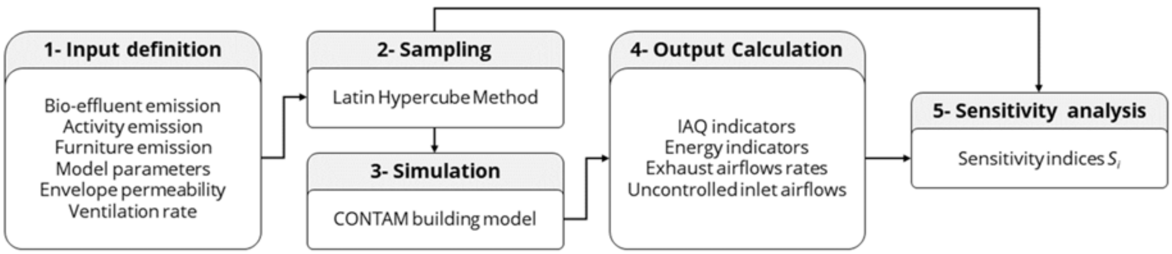

Figure 1: key steps for the sensitivity analysis

2.1 Case study

The case study, illustrated in Figure 2, is a low-energy, two-storey house fitted with balanced mechanical ventilation with heat recovery (MVHR) with constant airflows. The total occupied area of the building is 135 m², with a ceiling height of 2.50 m. The house has 4 bedrooms (BR1, BR2, BR3, BR4), one bathroom per floor (BTH1, BTH2) and a kitchen opening onto the living room (LVR/KTC).

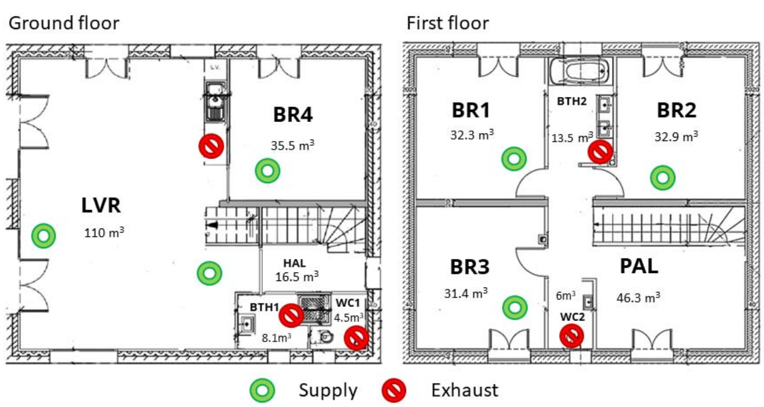

Figure 2 : Plan of the case study house; supply and exhaust location for MVHR; exhaust location only for MEV

According to the ventilation performance assessment method tested, the occupancy of the house was considered to be 5 people. The schedules associated with (Poirier et al., 2021a) for occupancy with the daily time spent by the occupants in the rooms were used, with, for example, 2h10 in the kitchen, 9h20 in the bedroom, and the occupancy state awake 14h40 per day.

Five ventilation systems were implemented in CONTAM model and implemented on French low energy house case study (Poirier et al., 2021b, 2022a) :

MEV-CAV, for mechanical exhaust-only ventilation with constant air volume

MVHR-CAV, for mechanical balanced ventilation with heat recovery and constant air volume

MEV-RH, for mechanical exhaust-only ventilation and humidity control,
MVHR-RB, for mechanical balanced ventilation with heat recovery and CO2 & humidity control at the room level
MEV-RB, for mechanical exhaust-only ventilation and CO_2 & humidity control at the room as an adaption of the MVHR-rb,,

2.2 Input définition

Based on lessons learnt from previous simulation work to assess ventilation performance (Poirier et al, 2022a, 2022b), twelve inputs were difined by category :

- Occupancy pollutant emissions,

Bio-eff, the considered bio-effluents are CO_2 and H_2O, they are released into the room where the occupant is located. The resulting input is a float variable varying within the range of 0 (for a low emission occupant) to 1 (for a high emission occupant).

- Activity and furniture pollutant emissions

Acti-H2O, Acti-PM25, Furn-HCHO the activity and furniture emissions rates, we include emissions of H_2O (cooking, shower, laundry, laundry drying), $PM_{2.5}$ from the occupants' activity (cooking) and HCHO from furniture and building materials. For H_2O, the emissions rates of all activities are assumed to be corelated and to vary from -30% to + 30% of the reference scenario. Consequently, the resulting input for the H_2O activity is a float variable, varying in the range 0.70 (for -30%) to 1.30 (for +30%). For the $PM_{2.5}$ activity the float variable named varying in the range 1.26 to 2.55 and referring to the $PM_{2.5}$ emission rate due to cooking activities (Poirier et al., 2022a, 2021a). For HCHO, the emission rates per m² of floor area will vary from the lowest scenario of 4.5 $\mu g.h^{-1}.m^2$ to the highest scenario 23.6 $\mu g.h^{-1}.m^2$). Again, a float variable is introduced, and varies in the range 4.5 to 23.6, referring to the furniture emission rate.

- CONTAM model parameters

Mbuff, materials in buildings may influent the humidity in air depending on the composition of walls, furniture, floor, etc. This is because materials can absorb and release moisture over time that corresponds to the hygroscopic buffer effect. Here the hygroscopic buffer effect is described with the boundary layer diffusion model in CONTAM as a source/sink element. Two inputs are used: Mbuff-L (for Model buffer in Low adsorbing rooms) and Mbuff-H (for Model buffer in High absorbing rooms), float variables varying respectively from 0 to 0.25 and 0.75 to 1.

MPM2.5-vd, MP2.5-r the CONTAM model parameters for deposition velocity and the resuspension rate. We have selected two $MPM_{2.5}$ inputs for the sensitivity analysis: the deposition velocity model $MPM_{2.5}$-vd in the low and high range based on min (0.3 $m.h^{-1}$) and max (1.8 $m.h^{-1}$) values measured in houses with furniture in (Fogh et al., 1997; Thatcher and Layton, 1995), and the resuspension model $MPM_{2.5}$-r varying within min (4.4 $.10^{-7}$ h^{-1}) and max (1.8 $.10^{-5}$ h^{-1}) values measured in (Thatcher and Layton, 1995). For both MPM25 inputs we propose to use the median as the reference value.

Perm, the air leakage level through the envelope, we therefore propose a input varying in the range [0.05; 0.9] corresponding to the q4a airleakage level. According to data measured over 126,840 single family houses in France (116,847 with exhaust ventilation, 6,736 with balanced ventilation) the median q4a is around 0.4 h-1 varying within the range 0.05 h^{-1} to 0.9 h^{-1} for extreme data (excluding outliers ±2.7 times the standard) (Mélois et al., 2019).

- Ventilation systems and strategies

Q-exh, Q-max two inputs varying in range [0.7; 1.3] focused on the exhaust airflows that could be adapted to the five ventilation systems modelled. The first one, Q-exh, is a constant multiplier coefficient to modify the total exhaust airflow and is applied to all exhaust paths in the CONTAM model (kitchen, bathrooms, toilet). The second input, Q-max, is a constant multiplier coefficient applied only to the maximum airflow Max/Qboost control value For MVHR systems the supply airflows were adjusted to correspond to the Q-exh or Q-max edited exhaust airflows, in order to keep the balance between exhaust and supply.

2.3 Output calculation

To evaluate the most important inputs and the uncertainty of the ventilation performance assessment methods the first selected outputs were five IAQ performance indicators (**I_{CO2}**, **I_{HCHO}**, **I_{PM25}**, **I_{RH70}**, **I_{RH30_70}**) of the method (Poirier et al., 2021b). These five indicators were then extended with two additional IAQ indicators for formaldehyde and $PM_{2.5}$ short-term exposure risks (**I_{HCHO-s}**, **I_{PM25-s}**) and one energy indicator evaluating the thermal heat loss from supply airflows and uncontrolled infiltration (**I_{Ewh}**) calculated with equation 1

$$I_{Ewh} = \mathrm{H_{th}} = \frac{C_{pm}}{3600}.\left(1-\varepsilon_{heat_{ex}}\right)\int q_m(t).\left[T_{in}(\mathrm{t}) - T_{ex}(t)\right].dt \tag{1}$$

with **I_{Ewh}** the energy indicator resulting directly from H_{Th} , the heat losses from exhausted air *[kWh]*, q_m the total exhaust mass airflows in *[$kg.s^{-1}$]*, C_{pm} the heat capacity of air (we used 1 $kJ.kg^{-1}.\ °C^{-1}$), $\varepsilon_{heat_{ex}}$ the heat exchanger efficiency assumed to be ideal and constant. A constant theoretical efficiency of 0.8 can, for example, be used for MVHR and 0 with no heat recovery. T_{in} is the zone temperature where the air is exhausted, and T_{ex} the external temperature *[°C]*.

In addition, a variant of I_{CO2} was tested, with a variable exposure threshold based on a complementary input T_{CO2}. This variant was referenced as I_{nCO2}-v the maximum cumulative CO_2 exposure over T_{CO2} ppm in the bedrooms, with T_{CO2} included in the sampled variable input varying in the range [800; 1200].

All these IAQ and energy indicators are proposed with an associated acceptable threshold (AT) representing a reference limit of acceptable performance not to be exceeded. For results analysis the indicators were normalised by their AT and referenced with the notation [In -].

2.4 Summary of Inputs and Outputs

The selected 12 inputs and 9 outputs for the sensitivity analysis are summarised in Table 1-2, with their associated range of variation. The reference column, gathers reference or average values for all inputs.

Inputs	Description	Low	Reference	High
Bio-eff	occupant CO_2 and H_2O emissions	0	0.333	1
Acti-H_2O	moisture emissions from activities	0.7	1	1.3
Acti-$PM_{2.5}$	emissions from cooking activities	1.26	1.91	2.55
Furn-	HCHO formaldehyde emissions from furniture	4.5	12	23.6
Mbuff-L	buffer effect for low adsorbing room	0	0	0.25
Mbuff-H	buffer effect for high adsorbing room	0.75	1	1
$MPM_{2.5}$-vd	Deposition velocity	0,3	0,65	1,8
$MPM_{2.5}$-r	Resuspension rate	$4.4\ .10^{-7}$	$9.90\ .10^{-7}$	$1.8\ .10^{-5}$
Perm	Airleakage level based on a q4a	0.05	0.4	0.9
Q-exh	Total exhaust airflow multiplier	0.7	1	1.3
Q-max	Maximum airflow M/Qboost multiplier	0.7	1	1.3
T_{CO2}	Variable CO_2 exposure AT for I_{nCO2-v} calculation	800	1000	1200

Table 1 : Summary of the proposed inputs for the sensitivity analysis

Outputs	Description	AT
I_{nCO2}	Maximum cumulative CO_2 exposure over 1000 ppm	1000 .*d* (ppm.h)
I_{nCO2-v}	Maximum cumulative CO_2 exposure over T_{Co2} ppm	T_{Co2} *d* (ppm.h)
I_{nHCHO}	Maximum cumulative HCHO exposure among all the occupants	9.d (µg.m^{-3}.h)
$I_{nHCHO-s}$	Maximum occupant HCHO exposure over a one-hour average period	100 µg.m^{-3}
I_{nPM25}	Maximum cumulative $PM_{2.5}$ exposure among all the occupants	10.d (µg.m^{-3}.h)
$I_{nPM25-s}$	Maximum occupant $PM_{2.5}$ exposure over a 24-hour average period	25 µg.m^{-3}
I_{nRH70}	Maximum percentage of time with RH > 70% among all the rooms	18%; 10.8%;1.8%
I_{nRH30_70}	Maximum percentage of occupant time spent with RH outside the range [30-70%]	14.4%
I_{Ewh}	Heat losses from total exhaust airflows	-
Q-exh	Total exhaust airflow multiplier	0.7
Q-max	Maximum airflow M/Qboost multiplier	0.7
TCo_2	Variable CO_2 exposure AT for I_{nCO2-v} calculation	800

Table 2 : Summary of the proposed outputs for the sensitivity analysis

2.5 Simulation process :

The simulations were performed with CONTAM, a multi-zone modeling software developed by the National Institute of Standards and Technology (NIST). It is used in a wide range of applications, such as IAQ analysis, ventilation flow management and smoke propagation, and has been extensively validated (Walton and Emmerich, 1994).The whole process was then automated with Python scripts for sampling, running the simulations and output data saving. The inputs were sampled before the simulations using Latin Hypercube Sampling methods (Helton and Davis, 2003) following the sampling method recommended in the EASI RBD-FAST sensitivity analysis method (Goffart et al., 2015; Goffart and Woloszyn, 2021). This sampling was carried out with a Python function implemented in the SALib library.

The simulation included 500 simulations per ventilation system, for a total of 2,500 simulations carried out over the heating period from October 15, 00:00, to April 14, 12:00, i.e. 4466 hours, with time steps of 10 min depending on the heating period. Using CONTAM, which has reasonable computational costs, the simulation time was around 36h for the 2500 simulations, calculated with an Intel Core i5-7200U CPU @ 2.50GHz, 2712MHz, 2 cores and 8 GB RAM

In the EASI RBD-FAST method used, the sensitivity indices (**Error! Reference source not found.**) were the first-order indices from the popular Sobol method based on the variance decomposition of the model's output (Tarantola et al., 2006; Plischke, 2010; Tissot and Prieur, 2012; Goffart et al., 2015).

$$S_i = \frac{V[E[Y|X_i]]}{V[Y]} \tag{2}$$

with X_i the input random variable sampled with the LHS method for $i = (1, \ldots, \mathrm{k})$ the number of inputs; $Y = f(X_1, \ldots, X_k)$ output of the model; S_i the first-order sensitivity indices of input i; $E[Y|X_i]$ the conditional expectation of Y given X_i, and $V[-]$ the variance of a random variable (Plischke, 2010).

The indices are between 0 and 1 and are the measure of sensitivity computed by the EASI RBD-FAST method. A high index indicates a strong relationship between the variation of X_i and the variation of the output Y. The total sum of S_i should be close to 1 and if it is significantly less than 1, this implies interactions between parameters (Goffart and Woloszyn, 2021). Finally, the S_i indices were calculated for all the tested outputs, to identify which outputs present the greatest uncertainty regarding the inputs variations.

3 RESULTS

3.1 IAQ and Energy performance

Figure 3 with normalized indicators shows in the form of boxplots all the performance indicators calculated on the 500 simulations per strategy. In an overall analysis, the differences between strategies regarding IAQ performance appear relatively small and dependent on the pollutant. While the energy benefits present significant differences.

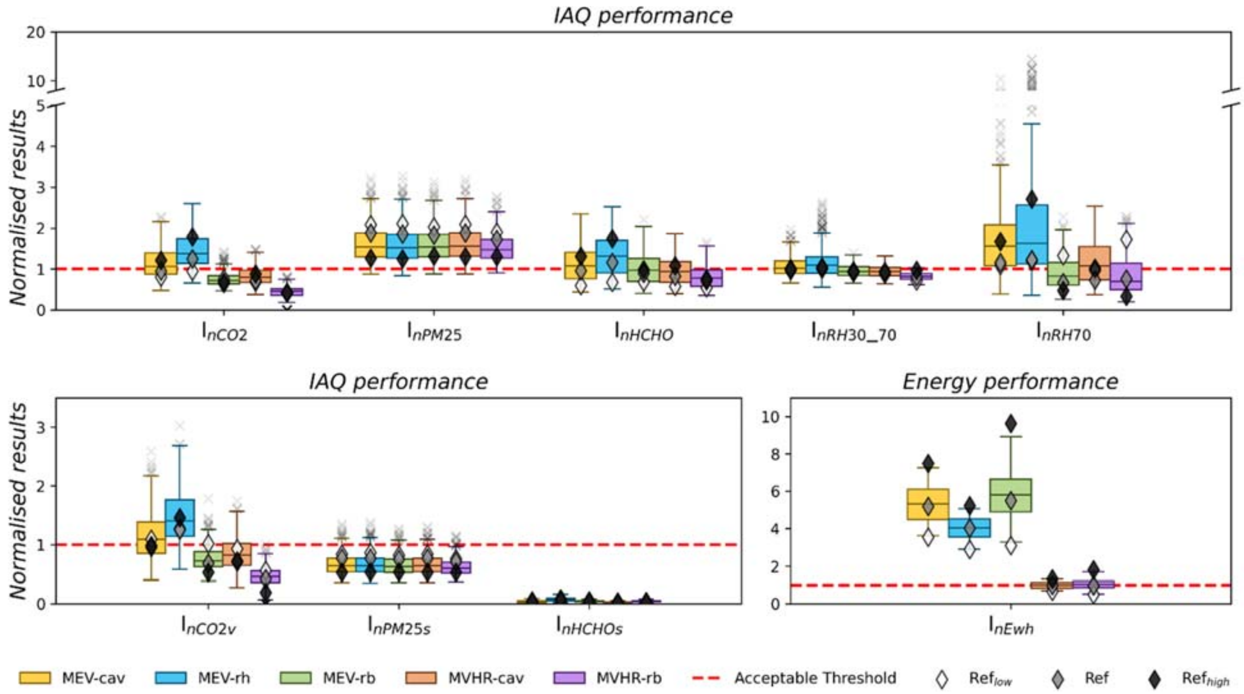

Figure 3 : Boxplot of normalized indicator performance results over the 500 simulations for the 5 ventilation strategies

The I_{nCO2} indicator confirms the good performance of MEV-rb, MVHR-rb and MVHR-cav, while I_{nCO2} remains mainly below the acceptable threshold. For MEV-cav and MEV-rh, the situation is different: in some simulations (e.g. for some inputs), the value of the indicator is lower than the threshold while in other cases it is higher. This position around the acceptable threshold depending on the input values is also observed for I_{nHCHO}, I_{nRH30_70}, I_{nRH70}. For $PM_{2.5}$ performance, no strategy reaches the acceptable thresholds except in certain aberrant configurations. The outliers also show that the combination of specific inputs could generate a factor of 3 between the lowest and highest values in most cases. In some cases, this could even generate huge differences in performance ratings, up to 14 times the acceptable threshold for MEV-rh on the In_{RH70}.

The additional QAI outputs for short-term exposures I_{nHCHO}-s and I_{nPM25}-s, for this case study and with the tested inputs, provide almost the same information as their long-term counterpart. For the short-term $PM_{2.5}$ risk, with the exception of a few outliers, the q1, q3 and median values are below the acceptable thresholds; the chosen duration of the 24-hour average period for short-term exposure may not be appropriate to capture the maximum exposure risk. Using a variable threshold between 800 and 1200 ppm for calculating CO_2 exposure I_{nCO2}-v also gives the same information as I_{nCO2}, with 1000 ppm. This means that in this configuration, a lower (or upper) limit of CO_2 exposure does not significantly increase (nor reduce) the assessed exposure of occupants.

Finally, to normalize the energy indicator I_{Ewh} we decided to use the MVHR-cav strategy as a comparison reference and used the median performance result obtained over the 500 simulations, with the median I_{Ewh} of the MVHR- cav equal to 543 kWh (4.02 kWh.m^{-2}). This normalization therefore shows that the energy requirements resulting from heat losses are for the 3 MEV strategies (MEV-cav, MEV-rh, MEV-rb) between 3 times and 10 times higher in comparison to the heat losses of the MVHR-cav strategy. But the comparison between MEV and MVHR is not particularly relevant: most of the energy savings come from the theoretical heat recovery efficiency of 0.8. However, this still highlights the fact that MEV-rh had lower energy losses than MEV-cav and MEV-rb, for IAQ performance equivalent to MEV-cav as noted above, but without the CO2 benefit provided by the MEV-rb. Finally, MVHR-rb, in some configurations, could be lower or higher than MVHR-cav, but had overall equivalent energy performance, with an additional advantage on all IAQ indicators compared to MVHR-cav and other MEV strategies.

3.2 Sensitivity Analysis

In this sensitivity analysis a total of 540 sensitivity indices (108 per ventilation strategy) were calculated across the 12 input variables and the 9 output indicators. Faced with the challenge of displaying the information from so many S_i, we built what we called a "flower graph" which groups all these 540 indices by ventilation strategy in Figure 3.

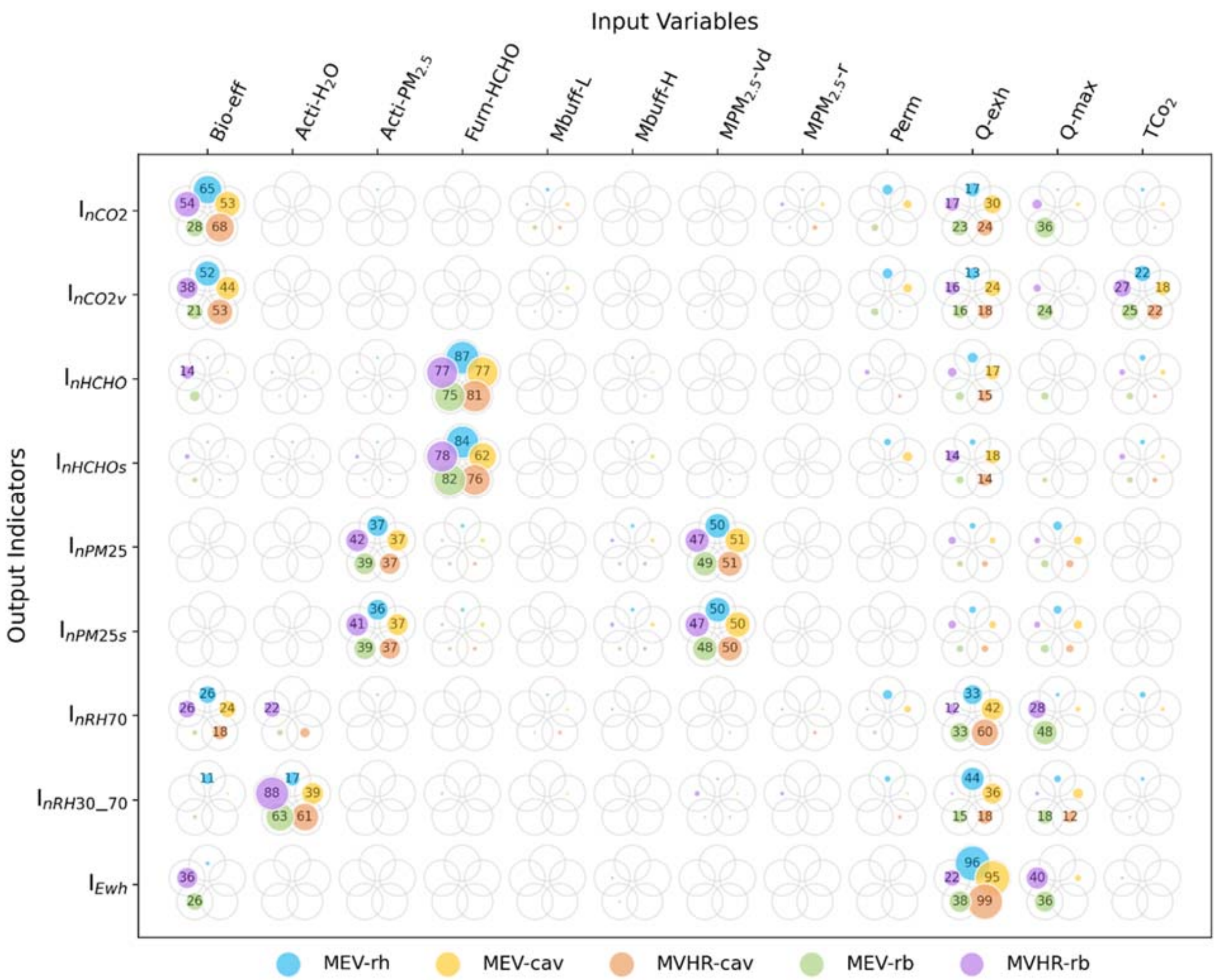

Figure 3 : Display of the sensitivity indices calculated for the 5 ventilation strategies

On this graph each row represents the output indicator and each column the input variable. Each of the 108 ”flowers” has 5 circles, one for each ventilation strategy. The grey circle represents the maximum possible S_i, with a coloured circle sized proportionally to its real value. Each colour representing one system. In addition, the percentage value (S_i%) is added if the indices start to be significant ($S_i > 0.1$) and the indices are not represented if $S_i < 0.05$. In other words, an empty flower means that for all ventilation systems the impact of the corresponding input variability on the output variability is insignificant, while coloured petals indicate important impact.

At first sight, the Mbuff-L, Mbuff-M, $MPM_{2.5}$-r and Perm input variables present little or no influence on the outputs for all the strategies (empty flowers on corresponding columns). Acti-H_2O, Acti-$PM_{2.5}$, Furn-HCHO, $MPM_{2.5}$-vd and TCo_2 influence one or two outputs, related to the pollutant associated with the specific input. The last inputs Bio-eff, Q-exh has a spread influence on several outputs. In the detailed of the sensitivity indices *Si* values, I_{nCO2} and I_{nCO2v} are impacted mainly by the Bio-eff inputs; from 0.28 to 0.68 for I_{nCO2} and from 0.21 to 0.53 for I_{nCO2v} depending on the strategy. Additionally, I_{nCO2} is also impacted by Q-exh with sensitivity indices from 0.17 to 0.3 depending on the strategy. I_{nCO2v} is the only output influenced by TCO_2 with sensitivity indices between 0.18 - 0.27 depending on the strategy, but Bio-eff is still the most influential on the I_{nCO2} indicator. This confirms that in our case the use of variable thresholds for CO_2 exposure is not necessarily useful and does not provide any additional information.

Regardless the ventilation strategy, the formaldehyde indicator I_{nHCHO} is not surprisingly influenced by Furn-HCHO as it is the only formaldehyde source input. The same could be true for Bio-eff impact on the CO_2 indicator, as Bio-eff is the only input varying the CO_2 emission source from the occupants. More unexpectedly, Bio-eff has also some impact on formaldehyde indicator I_{nHCHO} (Si=0.14), and this for MVHR-rb system only. This can be explained by the ventilation control strategy for MVHR-rb based on CO_2 which is related to the occupant but also impacts formaldehyde concentrations. For constant ventilation airflows (cav) the Q-exh value also has some influence on I_{nHCHO}, which can be explained by varying airflow rates. For the $PM_{2.5}$ indicators the 5 systems are almost equally impacted by the particle emission rates (Acti-$PM_{2.5}$, Si in [0.47-0.51]) and the deposition velocity ($MPM_{2.5}$-vd, Si in [0.37-0.42]) but not by the resuspension rate ($MPM_{2.5}$-r, Si<0.05). This result highlights the need to focus on the deposition velocity for the $PM_{2.5}$ model, as implemented in CONTAM, as its impact on the I_{nPM25} indicator is even higher than the impact of emission rates (sensitivity indices of 47 to 51 % for deposition velocity and 37 to 42% for emission rates). Regarding humidity-based indicators, I_{nRH70} is more impacted by occupants’ emissions (Bio-eff), while I_{nRH30_70} is more impacted by activities emissions (Acti-H_2O). This result is quite unexpected; indeed, moisture emissions from activities were expected to impact I_{nRH70}. Moisture emissions from activities are more intense and intermittent and, as peak emissions, should have an impact on high humidity levels (RH> 70%). But this has not been observed in the sensitivity results. In addition, I_{nRH70}, is strongly impacted by the exhaust airflows Q-exh and Q-max.

Lastly, for the heat loss indicator I_{nEwh}, its variability is influenced by Q-exh for MEV-cav, MEV-rh and MVHR-cav. While for the systems with the most complex control strategy (MEV-rb and MVHR-rb), I_{nEwh} are almost equally impacted by the Bio-eff, Q-exh and Q-max. The presence of Bio-eff for *rb* strategies could again be explained by the CO_2 control for the room-based systems. Surprisingly, inputs related to moisture sources (Bio-eff and Acti-H_2O) have no impact on the energy performance for humidity-based control systems (MEV-rh and MVHR-rh).

4 CONCLUSION

These results allow the performance of IAQ and energy ventilation to be assessed over a wide range of tested scenarios, instead of the more usual reduced set of minimum, average and maximum scenarios.

The results of the sensitivity analysis showed that some identified inputs in CONTAM model could be set to default values, such as those used for humidity buffering and $PM_{2.5}$ resuspension. On the contrary, attention should be paid on the notable influence of inputs concerning bioeffluent emissions, $PM_{2.5}$ from cooking activity, humidity from activities, formaldehyde from furniture and construction materials and the speed of deposition of $PM_{2.5}$, on the performance indicators. This confirms the need for further research to obtain robust input parameters and precise knowledge of pollutant emission scenarios.

To extend this sensitivity analysis, further simulations could focus on more detailed scenarios. For example, bioeffluent emission rates could vary independently for each occupant or different 'family types' could be tested. For $PM_{2.5}$ activity, the cooking emission scenario can be modified by differentiating the days or types of meals prepared throughout the week, in order to test 'cooking habits' and/or by adding $PM_{2.5}$ sources in other rooms. Moisture-generating activities can also be modified independently to achieve greater accuracy and identify specific actions that have an impact on relative humidity.

Finally, by including these lessons on uncertainty, the evaluated performance of the ventilation system could be more robust because the impact of the inputs on the performance indicator is better controlled. This paves the way for the use of IAQ and energy performance indicators in multiple building simulations to test and compare design parameters in a decision-making process and for the inclusion of these performance-based methods in new standards and regulations in Europe and beyond.

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