Towards performance-based approaches for smart residential ventilation: a robust methodology for ranking the systems and decision-making

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ABSTRACT

Smart ventilation which provides air renewal thanks to its variable airflows adjusted on the needs can improve both indoor air quality (IAQ) and energy performance of buildings. However, such performance gains should be quantified with performance-based approaches. In this paper, we propose to extend the performance-based approach with a robust methodology to rank the ventilation systems performance. Such a methodology could be used in a decision-making tool at the design stage of buildings. Indeed, when simulations are carried out, we generally obtain a relative range of the theoretical performances, which should be achieved for each tested ventilation strategy. Nevertheless, it does not allow to rank the ventilation systems performances and to choose the most relevant one from an overall performance point-of-view. In this work the overall performance aspect was focused on IAQ and energy performance through five IAQ - and one energy - performance indicator.

We propose in this paper a simplified approach in 3 keys steps (Figure 1) adapted from existing robust assessment methods, to achieve a robust ranking of the systems based on the aggregation of performance indicators results using Simple Additive Method (SAW). In the present work, five ventilation systems have been tested with several sets of input parameters (500 simulations). In addition, three reference scenarios for input values (low, reference, high) were used for robustness assessment. We compared the ranking calculated with 500 simulations with the ranking calculated with three reference scenarios. The objective was to assess whether the three reference scenarios are sufficient to obtain a relevant ranking of ventilation systems or if more simulations are needed to achieve this goal.

Our results showed that the aggregation of the performance indicators with the SAW method is relatively accurate compared to the performance observed individually by each indicator. Then, the calculation of the design score with the minimax regret robustness method offers a clear advantage to highlight the difference between the ventilation systems, to rank them by including the uncertainty of several simulations. In addition, we show that the use of the three reference scenarios could be sufficient to obtain a relevant ranking of the ventilation systems, in comparison with 500 simulations. However, if the number of simulations is limited, we propose to perform in priority the reference scenario, for an "optimistic performance ranking", or the reference high scenario for a "conservative performance ranking". Nevertheless, if there are no constraint, we encourage the decision maker to simulate at least the three reference scenarios

and ideally 500 scenarios or more. The latter reinforces the validity of the calculated design score and ranking by including the uncertainty on input parameters.

KEYWORDS

Smart ventilation, residences, indoor air quality, performance, performance-based, energy

GRAPHICAL ABSTRACT

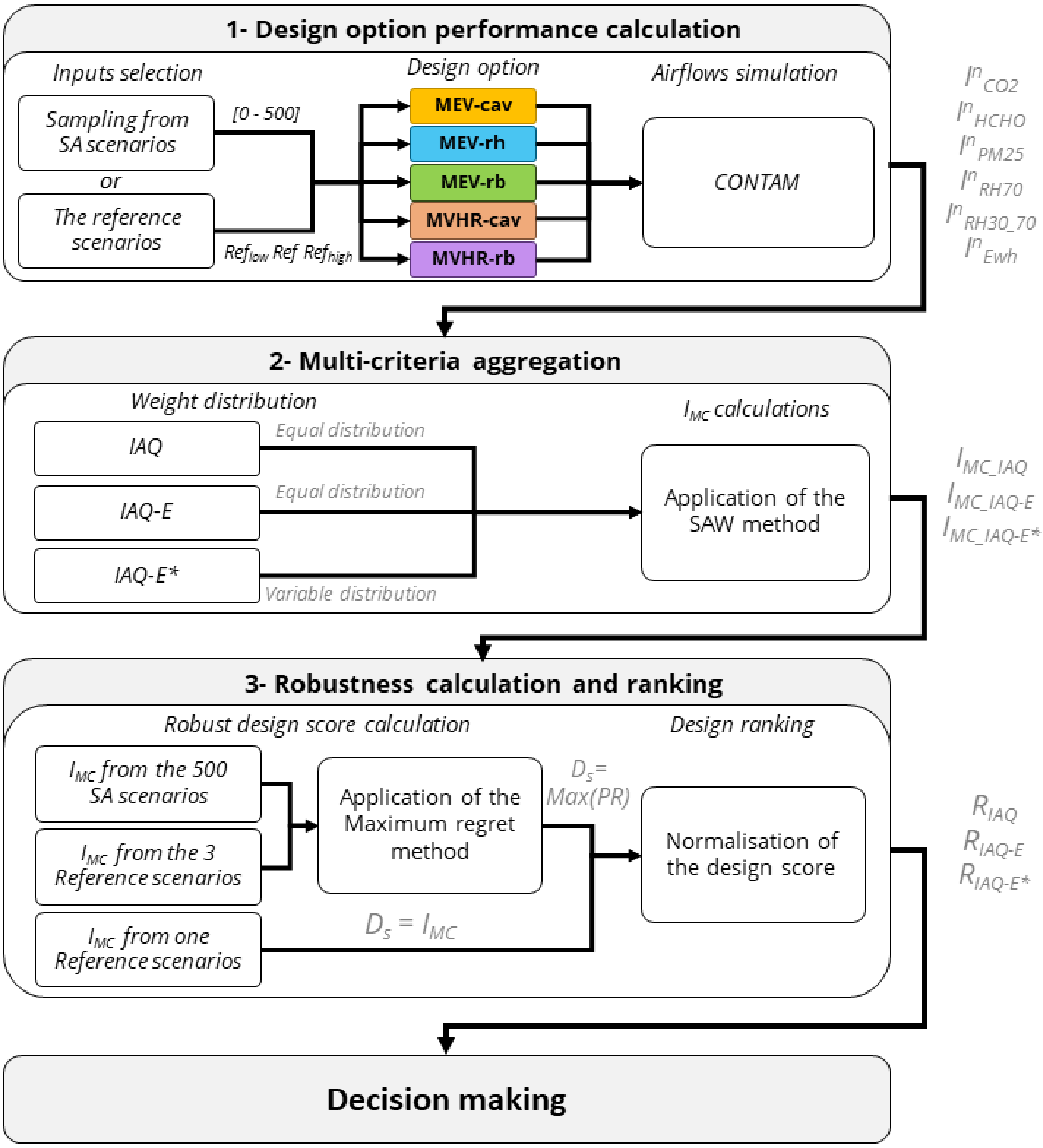

Figure 1 : Methodology for robustness calculation and ranking for decision making

1 INTRODUCTION

The assessment of ventilation performance often focuses on indoor air quality (IAQ). Nevertheless, with low energy buildings, the energy-saving potential from ventilation is becoming increasingly important. In addition, smart ventilation has been identified as a very promising way to improve both the indoor air quality and the energy performance of buildings, through the variation in time and/or place of ventilation airflows according to needs. Research efforts, such as those under in the framework of the IEA-EBC Annex 86, should make it possible to develop such smart ventilation strategies. It requires performance-based approaches in order to robustly assess the potential of gains, especially compared to more traditional constant-airflows ventilation strategies. These promising improvements need to be quantified in an overall performance way including IAQ, energy or even other relevant aspects. This paper only focusses on the IAQ and energy aspects of the overall performance of ventilation.

At the design stage, in a performance-based approach, the ventilation performance could be calculated by simulation. This assessment process consists in testing the performance of one (or several) ventilation systems according to one or (several) input scenarios; including pollutants emissions rates variations, occupant behaviours, building boundaries conditions. Due to the large possible variations in the input scenarios, we obtain a relative range of the theoretical performances. According to previous application case studies; testing IAQ or energy performance of constant and humidity controlled airflows ventilation (Poirier et al., 2022a, 2022b) ; the difference of the performances among the ventilation systems varies depending on the selected indicators. For example, differences between the ventilation systems were clearly identifiable for some indicators based on CO_2, on high relative humidity and on energy consumption. On the contrary, the performances were almost the same or very close for other indicators like the $PM_{2.5}$ and formaldehyde exposures. Nevertheless, it does not allow to rank the ventilation systems performances and to choose the most relevant one from a global performance point-of-view.

It clearly raises the question of:

How to aggregate performance indicators and balance IAQ and energy performance assessment to provide a robust ranking of the ventilation systems?

In this paper, we propose to explore a methodology to rank the systems performance including the uncertainty from simulations; in order to complement our method for overall performance assessment (MOPA) for ventilation (Poirier et al., 2021b).

2 METHODOLOGY

As a methodology, we propose a simplified approach based on 3 keys steps to achieve a robust ranking of the systems based on performance assessment results, to help in decision making (Figure 1-Graphical abstract). These steps are based on some relevant studies on existing robust assessment methods adapted to the building sector (Kotireddy et al., 2018; Velasquez and Hester, 2013; Hoes et al., 2009; Sharma and Bhattacharya, n.d.) that seem relevant for application in the context of MOPA development.

2.1 Design option performance calculation

The first step consists in performance assessment by simulations of the different design options (D_{opt}) to be tested. In building design, several parameters could be tested, such as thermal envelope materials, compactness ratio, external shadings, building orientation, heating systems, photovoltaic panels surface, etc. (Hoes et al., 2009; Kotireddy et al., 2017; Mechri et al., 2010).

In the present work, the design options are the ventilation systems and the performance calculation were performed with multi-zone CONTAM software which have been scientifically validated (Walton and Emmerich, 1994; Emmerich, 2001). With its models, CONTAM allows to describe for example ventilation airflows with complex strategies, indoor air pollutants, occupants exposure, building airtightness and more. For this step, we based our application on the performance calculated with 2500 simulations performed in (Poirier, 2023), with a sensitivity analysis (SA) experiment using the EASI RBD-FAST method (Goffart et al., 2015; Goffart and Woloszyn, 2021). From these simulations the performance results were calculated with the following performance indicators defined in (Poirier et al., 2021b; Poirier, 2023):

$\mathbf{I^n_{CO2}}$, Maximum cumulative CO2 exposure over 1000 ppm.

$\mathbf{I^n_{HCHO}}$, Maximum cumulative HCHO exposure among all the occupants

$\mathbf{I^n_{PM25}}$, Maximum cumulative PM2.5 exposure among all the occupants

$\mathbf{I^n_{RH70}}$, Maximum percentage of time with RH > 70% among all the rooms

$\mathbf{I^n_{RH30\_70}}$ Maximum percentage of occupant time spent with RH outside the range [30-70%]

$\mathbf{I^n_{Ewh}}$ Heat losses from total exhaust airflows 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 $\mathbf{I_{Ewh}}$ 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 this paper, five ventilation strategies (or referred as design option D_{opt}) 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 CO2 & humidity control at the room as an adaption of the MVHR-rb,,

For sensibility analysis, each design option 500 simulations were performed with variation on the input scenarios such occupant CO_2 and H_2O emissions, moisture emissions from activities, emissions from cooking activities, exhaust airflows and CONTAM $PM_{2.5}$ and moisture models parameters. The sampling of the 500 input scenarios was realised with the Latin Hypercube Sampling (LHS) methods (Helton and Davis, 2003) in accordance with the EASI RBD-FAST method (Goffart et al., 2015; Goffart and Woloszyn, 2021). This sampling was carried out with a Python function implemented in the SALib library.

In addition, three reference scenarios ($\mathrm{Ref_{low}}$, Ref, $\mathrm{Ref_{high}}$) were also used for robustness assessment (Poirier, 2023; Poirier et al., 2021a). The objective was to compare the ranking based on the overall performance calculated with the set of 500 input scenarios and the ranking calculated with the reference and the two extreme input scenarios. This is to assess whether the three reference scenarios are sufficient to obtain a relevant ranking of ventilation systems or if more simulations are needed to achieve this goal.

2.2 Multi-criteria-aggregation

Then, we used the SAW method for the multicriteria aggregation step, that is a simple aggregation weighting method which regroups the 5 IAQ indicators and the energy indicators under one value that we named IMC for "multicriteria" indicator.

The second step focuses on the method to be used to regroup the performance results from the six indicators to one aggregated value for each simulation. In the literature, the aggregation of several indicators for decision making could be found under the notion of *methods for "multi-criteria decision-making"* (MCDM)(Kotireddy et al., 2018; Namin et al., 2022; Velasquez and Hester, 2013). These methods generally propose a formulation to aggregate the multiple criteria for the tested design option under one value (here the performance indicator). We propose to name this aggregated value **I_{MC}** for Multi-Criteria Indicator.

According to the literature, there are numerous methods of MCDM, with for example at least 10 different methods identified in a recent review on MCDM (Namin et al., 2022). As the purpose of this work is not to test or compare all the possible methods; we decided to use the Simple Additive Weighting (SAW) method. This method is a common MCDM method widely used and seems relevant to our problem. Indeed, this method is a classical method consisting of adding up the indicators with a weighting coefficient to give more or less importance to certain indicators over others. The proposed calculation of I_{MC} with the SAW method (Equation 1) has been realised and adapted from the method described in (Podvezko, 2011).

$$I_{MC} = \sum_i \omega_i . I_i \tag{2}$$

Where ω_i is the weighted normalized value ($\sum \omega_i . = 1$) of the indicator I_i in [I^n_{CO2}, I^n_{HCHO}, I^n_{PM25}, I^n_{RH70}, $I^n_{RH30\_70}$, I^n_{Ewh}].

The weighted values can be set in several ways depending on the priority given to the indicator by the decision maker. To show the impact of weight arrangement priority on the I_{MC} calculation we build three weight distributions to calculate an associated I_{MC} (Table 1):

I_{MC_IAQ}, corresponding to decision-making based only on the IAQ indicator, with the weight equally distributed over the five IAQ indicators (I^n_{CO2}, I^n_{HCHO}, I^n_{PM25}, I^n_{RH70}, $I^n_{RH30\_70}$) and 0 for I^n_{Ewh} .

I_{MC_IAQ-E}, corresponding to decision-making for overall performance assessment based on IAQ and Energy aspects, with the weight equally distributed on the six indicators. However, this distribution gives globally an advantage to the IAQ aspect as energy aspect is represented only by one indicator against five indicators for IAQ.

I_{MC_IAQ-E*} corresponding to a decision making for overall performance assessment based on IAQ and Energy aspects, but with variable and unequally distributed weight on the six indicators in comparison with I_{MC_IAQ-E}. This distribution was built to have an equal proportion between IAQ and energy. Consequently, the weight of I^n_{Ewh} is set equal to 0.5. In addition, the IAQ aspects were differentiated to give more weight to the indicators I^n_{PM25} and I^n_{HCHO}. Their weight is doubled in comparison to the remaining IAQ indicators. This distribution for IAQ indicator could correspond to the assumption that moisture and CO_2 have less impact on the health in comparison with $PM_{2.5}$ and formaldehyde.

Distribution *For I_{MC} calculation*	**Weight ω_i**					
	I^n_{CO2}	I^n_{RH70}	$I^n_{RH30\_70}$	I^n_{PM25}	I^n_{HCHO}	I^n_{Ewh}
I_{MC_IAQ}	0.2	0.2	0.2	0.2	0.2	0
I_{MC_IAQ-E}	0.16	0.16	0.16	0.16	0.16	0.16
I_{MC_IAQ-E*}	0.071	0.071	0.071	0.143	0.143	0.5

Table 1 : Weight distribution for I_{MC} calculation

2.3 Robustness calculation and ranking

Lastly, the robustness calculation step consists in integrating into one design score (D_s) all the individual performance indicators I_{MC} across the tested scenarios. Then this robust design score can be used for performance comparison of each design option (D_{opt}).

According to the comparative study for robustness method assessment of Kotireddy (Kotireddy et al., 2019); several methods exist for robustness calculations. In this study three robustness assessment methods were implemented -max–min method, best-case and worst-case method, and minimax regret method - and compared with the widely used Taguchi method.

The Max-Min method evaluates the performance spread (PS) between the maximum performance ($A_{D_{opt}}$) and the minimum performance ($B_{D_{opt}}$) of each design strategy across all the scenarios. The most robust design is the design with the smallest PS.

$$PS = A_{D_{opt}} - B_{D_{opt}} \tag{3}$$

The best-case and worst-case method evaluates the performance deviation (PD) between the maximum performance ($A_{D_{opt}}$) and the minimum performance of all design strategies (D_{min}). The most robust design is the design with the smallest PD.

$$PD = A_{Dopt} - D_{min} \tag{4}$$

The minimax regret method evaluates the performance regret (PR), with the difference between the performance indicators value and the minimum performance of each scenario across all designs (C_s). The performance regret is calculated for each design strategy D_{opt} across all the scenarios s. Then the MPR is the maximum performance regret of each design, and the most robust design is the design with the smallest MPR

$$PR = I_{MC,Dopt,s} - C_s \,; with\ C_s = \underset{s}{\mathrm{Min}}(I_{MC(all\_Dopt),s}) \tag{5}$$

$$MPR = \underset{D_{opt}}{\mathrm{Max}}(PR) \tag{6}$$

The Taguchi method evaluates the robustness of the design strategies based on the mean and standard deviation of the performance indicators over all the scenarios. The most robust design is the design with the smallest mean and standard deviation (mean ⋂ std) (Hoes et al., 2009)

The max–min, best-case and worst-case, and minimax regret robustness methods for design score provide a better integration of the uncertainty across all the scenarios in comparison with the Taguchi method. That could facilitate the decision-making process by reducing the gap between simulated performance at the design stage and the real performance (Kotireddy et al., 2019).

All four methods presented above were tested for the calculation of the robust design score. Finally, we selected the minimax regret method for design score calculation and the final ranking. Indeed, the use of these three other methods had little impact on the final ranking and the minimax regret method has been identified as a less conservative approach to design decision making when risk can be accepted as a trade-off (Kotireddy et al., 2019). This is relevant for MOPA as compared to the other three methods which are more conservative.

Finally for the results analysis we calculated the design score by applying Equation 5 with the I_{MC} from the 500 SA scenarios on one hand and with the I_{MC} from the 3 Reference scenarios on the other hand. The last case is the reference scenario when the design score is directly the I_{MC}. Then this design scores were normalized In [%] by $\sum_{D_{opt}}(D_s)$ the sum of all the design scores. That facilitating the ranking and comparison between the weight distribution and the number of scenarios.

3 METHOD ANALYSIS AND RANKING RESULTS

The first step of the proposed robustness method consists in design option performance calculation and here we exploited the results from the 500 simulations per design option used for SA application case study (Poirier, 2023). The following sections next result analyses are focused on the second step (multi-criteria aggregation) and the third step (robustness design score calculation) for robust ranking.

3.1 Multi-criteria aggregation

In the Figure 2, we represent by boxplot the aggregate I_{MC} calculated with the three weight distributions (IAQ, IAQ-E, IAQ-E*) on the 500 simulated scenarios for each design option. The three reference scenarios are represented by small grey diamonds. The boxplots represent first quartile (q1) at the bottom of the box, the median in the middle and the third quartile (q3) at the top of the box; with the whiskers extend from the box by 1.5x the inter-quartile range (IQR) and the remaining outliers are represented by grey crosses.

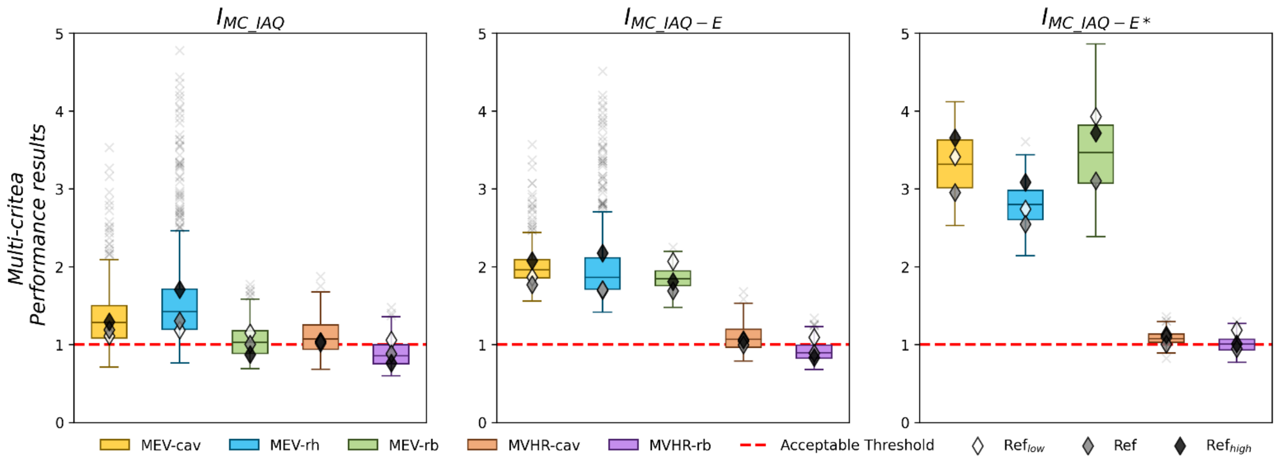

Figure 2 : Multi-criteria performance results of the five design option tested by weight distribution

This representation gives a general overview of the I_{MC} results depending on the proposed weight distribution. For the first weight distribution, including only the IAQ indicators, the aggregated performance (I_{MC_IAQ}) results in values mainly between 1 and 2 for MEV-cav and MEV-rh. For the MEV-rb and the MVHR-cav the results are centred around the acceptable threshold of 1. ; only the MVHR-rb gives the values mostly lower than 1, meaning an acceptable performance. The outliers for MEV-cav and MEV-rh illustrate that specific inputs scenarios for these systems could generate high performance assessment difference more than 4 times the acceptable thresholds in some cases. Fortunately, the results of the reference scenarios are not outliers, which would mean that these three reference scenarios are not at all representative.

For this first case, with constant weight distribution over IAQ only, there is no clear gap between the systems in comparison with the two others weight distribution results (I_{MC_IAQ-E} , I_{MC_IAQ-E*}). Such results may question the exclusive use of these IAQ indicators to rank the ventilation systems.

The introduction of the energy indicator in I_{MC_IAQ-E} underlines the difference between MEV and MVHR systems. Indeed, the values of I_{MC_IAQ-E} are distributed around the acceptable threshold of 1 for MVHR. On the opposite, the values for I_{MC_IAQ-E} are much higher than the acceptable threshold, being distributed around the value of 2 for all three MEV systems. In detail, a higher energy performance of MEV-rh (meaning lower I_{Ewh}) raised its global performance (lower $I_{MC-IAQ-E}$ median value) in comparison with the two other systems without heat recovery (MEV). This compensates a slightly lower IAQ performance for MEV-rh. Whereas the higher I_{Ewh} of the MEV-rb increased its $I_{MC-IAQ-E}$ value in comparison with the two other MEV. As a result, the three MEV systems have now comparable median values of I_{MC_IAQ-E}. Regarding the two MVHR systems, there is no significant change and the MVHR-rb still performs slightly better than MVHR-cav, thanks to its better IAQ performance. Thus, the distribution of IAQ-E weights highlights the energy benefit of heat recovery from MVHR systems.

In the last case IAQ-E*, with variable weight distribution, the differences between all systems are even more pronounced. Now, the MEV performance results are worse (I_{MC_IAQ-E*} range between 2.5 and 4). On the opposite, both MVHR systems exhibit performance indicator close to 1, with a narrow distribution range. In addition, the differences between the three MEV systems highlights that MEV-rh had lower energy losses than MEV-cav and MEV-rb. In this case, if energy saving is encouraged, the use of MEV-rh could be relevant in comparison with MEV-cav. In contrast if IAQ is prioritized on energy, the use of MEV-rb could be more relevant (as shows by IAQ-E distribution).

The comparison of these three weight distributions shows that the weight distribution is a clear leverage to increase the differences between systems on the final aggregated performance results. However, the uncertainty distribution from the 500 simulations performed and presented with boxplots doesn't makes systematically the ranking of the systems obvious. Moreover, in practice the use of weight distributions that voluntary increase the difference between systems to facilitate the ranking could lead to a wrong extrapolation of the simulated performance results. For example, this may question the ranking based on the IAQ-E* where the differences are mainly related to the initial pronounced differences on the I_{Ewh}.

That confirms the need of the robust design score calculation of the next step, considering uncertainty, to finalize the ranking process for decision-making.

3.2 Robust design score calculation and ranking

Figure 3 regroups, for the three tested weight distributions, the normalised design score [%] calculated with different scenarios. According to the methodology described above, the design score with 500 simulations and the three reference scenarios were calculated with the minimax regret method. The design scores for Ref_{low} , Ref, Ref_{high}, plotted in the figure, are directly the I_{MC} of each individual scenario. Then, for ranking, the best design option (n°1) is the one with the lowest design score and the last (n°5) is the highest design score.

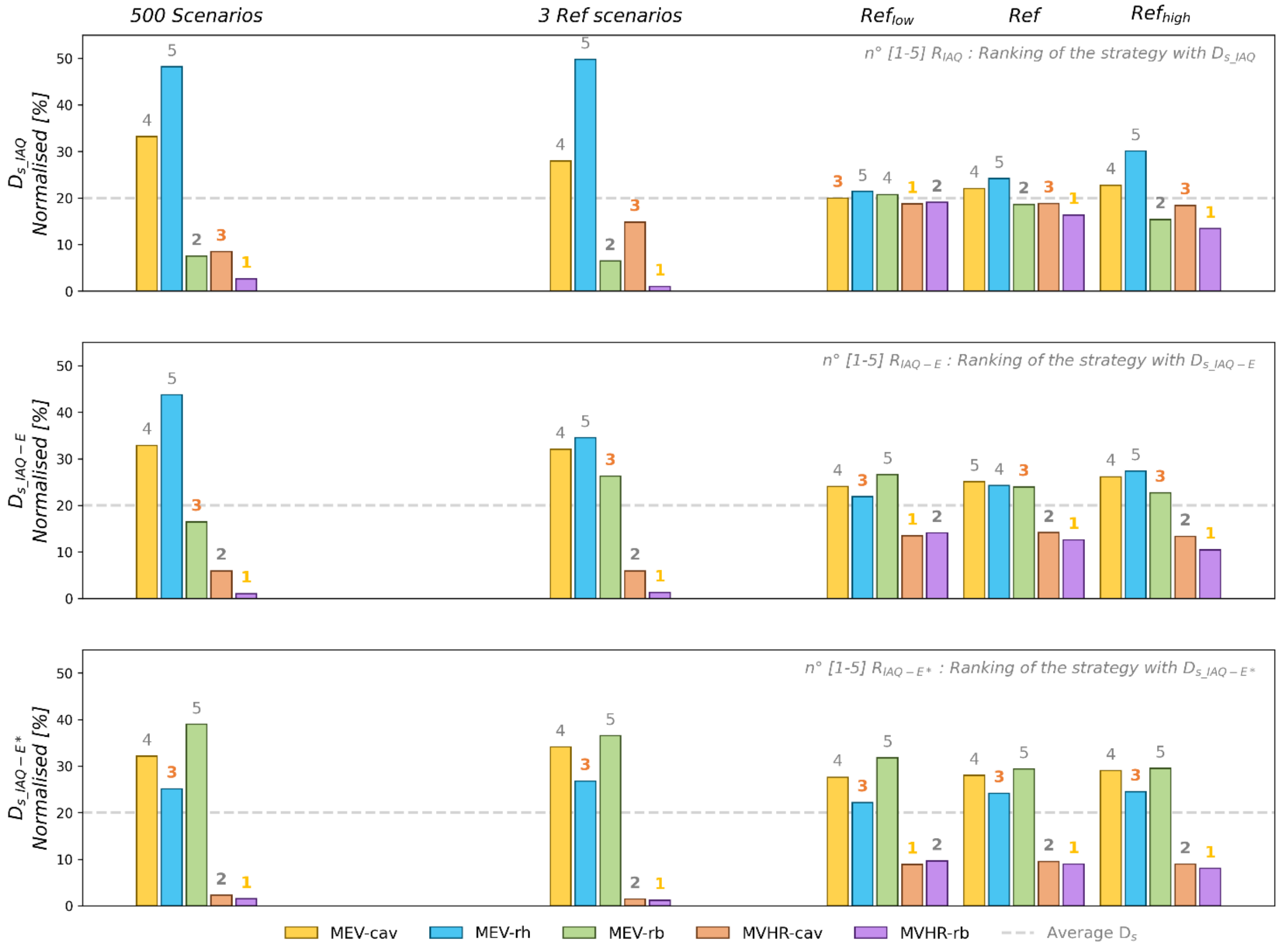

Figure 3 : Robust design score and ranking, MinMax regret method.
Different weight distributions are presented: equal IAQ (top), equal IAQ and Energy, IAQ-E (middle), and enhanced energy and health IAQ-E* (bottom).
Different scenarios are presented: 500 per system using uncertainty distribution on input parameters (left), three per system: high/ref/low (middle), and one per system, separating high/ref/low (right).

At first, the ranking order calculated from the design score is the same with 500 simulations and the 3 ref simulations. This confirms previous observations made on outliers of Figure 2 with the reference scenarios (grey diamonds) located inside the q1-q3 box. It means that the use of these 3 references scenarios for design score calculation and ranking provides the same information as the one obtained with 500 simulations design score calculation and ranking.

In detail, the ranking with design score calculated from each individual scenario (right plots), changes sometimes depending upon the weight distribution and the scenario used. For example, the ranking is inversed between MEV-cav and MEV-rh with the Ref scenario depending upon weight distribution. Another example is the Ref_{low} scenario, where ranking inversion is observed between the MVHR-cav and MVHR-rb as compared to all the other cases. In general, with Ref_{high} scenario the differences between design scores are more identifiable than for the Ref_{low} scenario.

Based on these results and the analysis made on Figure 2 we propose to :

> *Exclude* the Ref_{low} scenarios from design scores for ranking. The risk is the loss of the uncertainty aspects, as this Ref_{low} ranking does not match with the ranking results obtained with the 500 simulations.

Keep the Ref scenario design score for an "optimistic performance ranking", indeed the I_{MC} performance results of this reference scenario are mainly close to the q1 value and the ranking.

Keep the Ref_{high} scenario design score for a "conservative performance ranking", indeed the I_{MC} performance results of this high reference scenario are mainly close to the q3 or the median value.

Associated together, the I_{MC} from Ref and Ref_{high} mainly cover the q1-q3 interquartile space (or at least the q1-mean). This allows to keep part of the uncertainty information and to calculate the design score with a ranking in accordance with the ranking of the 500 simulations.

Secondly, the impact of weight distribution on ranking is clearly identifiable with the design score. Indeed, the normalized design score is highly impacted for the MEV-rh from almost 50% (D_{s_IAQ}) to 25% ($D_{s\_IAQ\text{-}E*}$). An opposite evolution can be observed for the MEV-rb from almost 8% (D_{s_IAQ}) to 40% ($D_{s\_IAQ\text{-}E*}$). On the other hand, the results are only slightly impacted by the weight distribution for the MEV-cav (scores remaining around 32%), MVHR-cav (from 8% to 2%) and MVHR-rb (3% and lower). In all cases, MVHR-rb is ranked first and MEV-cav is ranked fourth, whereas MVHR-cav moves from third to second place due to the change in the ranking of MEV-rb.

This shows the importance of the weight given to the energy indicator and the priority balance between IAQ and energy. For instance, with the IAQ indicators only, the MEV-rb provides the second-best ventilation performance when it provides the worst one with the IAQ-E*distribution. Indeed, with the $D_{s\_IAQ\text{-}E}$, the better IAQ performance of the MEV-rb is penalized because of its higher energy consumption; this explains the swapping between change MEV-rb and MVHR-cav, the latter performing much better in energy consumption (thanks to heat recovery) for a slightly worse IAQ performance. On the opposite, the MEV-rh is by far the worst with IAQ performance only but it can reach a good third position with the IAQ-E* distribution. In this case, the 50% weight given for the energy indicator in the $I_{MC\_IAQ\text{-}E*}$ calculation valorizes the energy benefits of MEV-rh in comparison with the two other MEV systems which certainly provide a better IAQ.

4 CONCLUSION

To conclude, we propose a three-step method to rank different ventilation design systems and we tested it on five ventilation systems. We confirm that the performance indicators aggregation with the SAW method is relatively accurate compared to the performance observed by each indicator individually in previous study (Poirier et al., 2022a, 2022b; Poirier, 2023). Then, the calculation of the design score with the minimax regret robustness method offers a clear advantage to highlight the difference between the ventilation systems, in order to rank them by including the uncertainty of several simulations.

In addition, we show that the use of the three reference scenarios could be sufficient to obtain a relevant ranking of the ventilation systems, in comparison with the ranking obtained with 500 simulations. However, if the number of simulations is limited, we propose to perform in priority the reference scenario (Ref), if the decision making needs an "optimistic performance ranking", or the reference scenario with the highest emission rates (Ref_{high}) for a "conservative performance ranking". Nevertheless, if there are no constraint, we encourage the decision maker to simulate at least the three reference scenarios and ideally 500 scenarios or more. The latter reinforces the validity of the calculated design score and ranking by including the uncertainty on input parameters.

For the MOPA, we do not retain the IAQ weight distribution as it doesn't include energy aspects for OPA. We propose to use at this stage the IAQ-E distribution in a conservative approach with balanced distribution across the six selected performance indicators. However, the IAQ-E* present a strong interest for a decision maker that would need a strictly equal proportion between IAQ and energy aspects. In future work it could be relevant to perform a more detailed sensitivity analysis on the weight distribution and then elaborate an adapted weighting selection method specifically for the six indicators (or more if added). Other MCMD could also be tested for indicators performance aggregation.

In our case, the MVHR systems presented the best overall performance with an IAQ benefit of the smart ventilation strategy (MHVR-rb). Then, depending on the decision maker priorities, the third most performant system could be the MEV-rb if IAQ is favored, or the MEV-rh or if the energy savings are more essential. In both cases the variable smart ventilation strategies present a benefit over the constant MEV-cav.

Lastly, at this stage, this ranking of the ventilation strategies shouldn't be considered as general performance ranking valid in all buildings. Indeed, the method has been applied only on one case study to demonstrate the relevance of the proposed methodology as a robust performance assessment decision-making tool for ventilation systems in buildings at the design stage.

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