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A novel Monte Carlo modelling method to support control strategies development in building ventilation

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Abstract. Ventilation is critical for maintaining thermal comfort and air quality in buildings. However, developing ventilation control is challenging due to the large number of control variables and performance criteria. Typical ventilation controls are On-Off controls, time schedules, and PI/PID controls. Specific parameters are tuned based on simple rules of thumb and the engineer's experience. Although building simulation tools are commonly applied, they are normally used to evaluate the performance of certain control strategies rather than guide the development of these control strategies. This study presents a novel Monte Carlo modelling method that supports the early-stage development of ventilation control. The method consists of the following steps: (1) Creating an initial building model, (2) Identifying relevant control variables and assigning probability distributions, (3) Executing Monte Carlo simulations, (4a) Applying filters to assess the outcomes, (4b) Performing sensitivity analysis on control variables, (5) Selecting a ventilation control strategy fulfilling control objectives. The method is tested on a classroom equipped with a hybrid ventilation system. The case study demonstrates that the novel approach, allows ventilation designers to systematically identify high-performance control solutions for multiple control variables and performance requirements. Thus, offering clear advantages over the traditional trial-and-error method.

1 Introduction

Ventilation is one of the most important systems for maintaining thermal comfort and air quality in buildings. Hybrid ventilation combines mechanical and natural forces in a dual-mode system [1]. The active mode adapts to both indoor and outdoor conditions and takes maximum advantage of ambient conditions. Compared to natural ventilation or mechanical systems, hybrid ventilation systems consist of more controllable elements, such as operable building envelopes, HVAC systems, and room sensors. However, the control of these elements is a challenging task because of complex interactions between systems, dynamic outdoor and indoor conditions (e.g., outdoor air temperature, noise, air quality, and occupancy behaviour), and multiple control objectives (e.g., energy and comfort) [2].

Numerous control techniques for hybrid ventilation have been developed over the past decades. The control techniques are typically categorized into two layers: local control and high-level control [2]. Local control includes classic On-Off control and proportional-integral-derivative (PID) controller [3, 4], where specific parameters are tuned based on simple rules of thumb and the system design expertise. The limitation of local control is that they lack systematic methods for optimal technique integration, and are sensitive to the changes of exterior and interior conditions [5]. While high-level control is an additional layer of control to determine the references to the local control using specified rules, optimal control, such as model predictive control [6-10] and reinforcement learning[11, 12], or other computational intelligence such as fuzzy logic [13, 14]. Data-driven models, which automatically learn from real-world collected data of building and system dynamics and local disturbances (weather conditions and occupant behavior) are contingent on data availability and quality. These models are not always suitable for developing control strategies in the early phases. Commonly, physical-based models are employed to develop and test control strategies. These models use building simulation tools to capture the dynamics of building physics and systems, enabling adaptation to disturbances. While building simulation models are frequently utilized, their primary role tends to be evaluating control strategy performance rather than guiding control strategy development, particularly during the initial stages.

This study presents a novel method to support the development of ventilation control strategies that overcome the above-mentioned challenges. The method is based on Monte Carlo simulations to explore the control space and uses sensitivity analysis to identify critical control variables and support decision-making processes. The proposed method is tested on a typical classroom located in Oslo, which is equipped with a hybrid ventilation system.

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2 Methodology

The workflow of the methodology is shown in Fig. 1 and described in detail in the following sections.

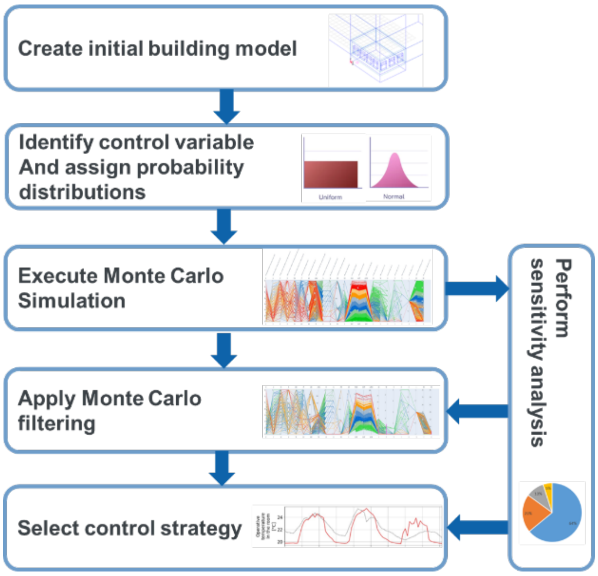

Fig. 1. Workflow for stochastic modelling method for control development

2.1 Creating an initial building simulation model

The initial building simulation model includes a detailed setup of building envelops, systems and building usage. However, detailed control strategies are not considered and only the basic concept for building HVAC operation is implemented. For example, in the initial model we need to define the ventilation principles whether it is natural, mechanical or hybrid ventilation, but do not need to specify control variables like setpoints and running hours. The initial model serves as the starting point from which the engineers or designers explore variations on control strategies.

2.2 Identifying relevant control variables and assigning probability distributions

There is a large number of variables that can be used to control ventilation. Based on the literature review by Peng et al. [2], the control variables can be classified into four categories: indoor environment, outdoor climate, building/system, and occupancy. The selection of inputs (control variables) is one of the most significant steps, where inadequate input coverage may overlook key parameters, while an excessive number of inputs can consume significant time and resources for computation.

Once relevant control variables are identified, the next step is to assign a probability density function to each control variable. Generally, four primary probability density functions are used in building simulations: normal/lognormal, triangular, uniform, and discrete/steps [15]. Uniform and discrete functions are often used for design or control parameters (e.g., window opening ratio), which assign equal likelihood to all values within a specified range. Normal or triangular functions are typically applied to parameters involving aleatory or epistemic uncertainty (e.g., occupancy density and occupancy schedule), which allows for a wide range of values while emphasizing the likelihood of certain values. For each variable, the range and probability distribution may depend on the building function, technical possibilities, user preference, economic considerations or other issues.

2.3 Executing Monte Carlo simulations

Monto Carlo simulations enable the exploration of an extensive control space by generating numerous random samples based on input variable distributions. These samples are then used as inputs for the building simulation model, and outputs, such as energy use, thermal comfort, air quality, etc., are recorded across multiple simulations. By aggregating these iterations, Monte Carlo simulations produce a range of possible outputs and reveal the correlations between inputs and outputs, which enables the development of robust control strategies adapted to various conditions.

Several sampling methods have been used in Monte Carlo simulations, including random sampling, Latin hypercube sampling, and quasi-random sampling (for example, Sobol sequence) [18, 21, 25]. The Sobol sequence method is used in this study because it is an efficient space-filling technique to produce low discrepancy sequences by filling multidimensional spaces with uniform coverage in the unit hypercube. The samples are chosen under consideration of the previously sampled points and thus avoids the presence of clusters and gaps [26]. In addition, it is possible to increase statistical convergence when compared to the random sampling method [16].

2.4 Applying filtering to assess the outcomes

Monte Carlo simulations produce a wide range of possible outputs. Engineers or designers need to further define what performance should be achieved by the ventilation systems, in terms of energy use, thermal comfort and air quality, and other considerations. The performance criteria could be based on international standards, national regulations, or specific requirements set by the clients. By using the performance criteria as filters, it could divide the outputs into two subspaces, corresponding to behavioral and non-behavioral outputs. Monte Carlo filtering is based on factor mapping setting, which helps to identify regions of the input space that meet certain criteria [25].

Parallel coordinate plot (PCP) is an interactive tool to visualize control space and support the decision-making process. Each vertical bar represents a variable and has its own distribution. Adjusting the filters allows to identify suitable settings for control variables to achieve the desired performance. Fig. 2 illustrates a case study with 10,000 simulations. By applying the filter on overheating hours, high CO_2 level hours, and ventilation capacity, only 683 behavioral simulations remain, as shown in Fig. 2. PCP is effective when exploring and analyzing multivariate data. However, if the analysis contains more than approximately 10 variables, it becomes challenging to identify which variables have a significant impact on the output by applying the filter [27]. Therefore, sensitivity analysis is needed to eliminate non-significant control variables.

2.5 Performing sensitivity analysis

Sensitivity analysis allows to identification of the most influential control parameters and shows insignificant control parameters that can be ignored. Several different mathematical methods for sensitivity analysis can be found in the literature [21, 25]. In general, they can be distinguished by multiple dimensionalities, e.g., local/global, quantitative/qualitative, one-at-a-time/all-at-a-time [28]. The sensitivity analysis method TOM is used in this study, which was developed based on the Kolmogorov-Smirnov two-sample statistics [27]. This method can be used to rank inputs according to their influence on one or more outputs, which is suitable for identifying critical control variables that have a significant impact on one or more performance criteria.

2.6 Selecting a ventilation control fulfilling control objectives and performance criteria.

Sensitivity analysis assists engineers and ventilation designers simplify the decision-making process by fixing the non-influential control variables and highlighting the variables requiring special attention. By interactively adjusting the Monte Carlo filter, it could identify the regions of control space fulfilling the performance criteria. Subsequently, engineers and ventilation designers should select a control strategy among the control space aligned with project-specific objectives, for example, considering technical and economic factors.

Moreover, control strategies should adapt to the change of requirements during a year, for example, indoor comfort temperature criteria may vary between summer and winter seasons. Therefore, it is recommended to select and compare control strategies at different time resolutions (annual, two seasons, four seasons, or even monthly) based on control objectives. This comprehensive approach ensures that the chosen strategies effectively align with the dynamic needs of the building across varying time frames.

3 Case study

The proposed methodology is tested on a typical classroom to demonstrate the applicability of the method in practice. The initial building model is created using BSim, a commonly applied building simulation software for analyzing indoor climate and energy performance [16]. The classroom is located in Oslo, Norway. It has a rectangular shape with dimensions of

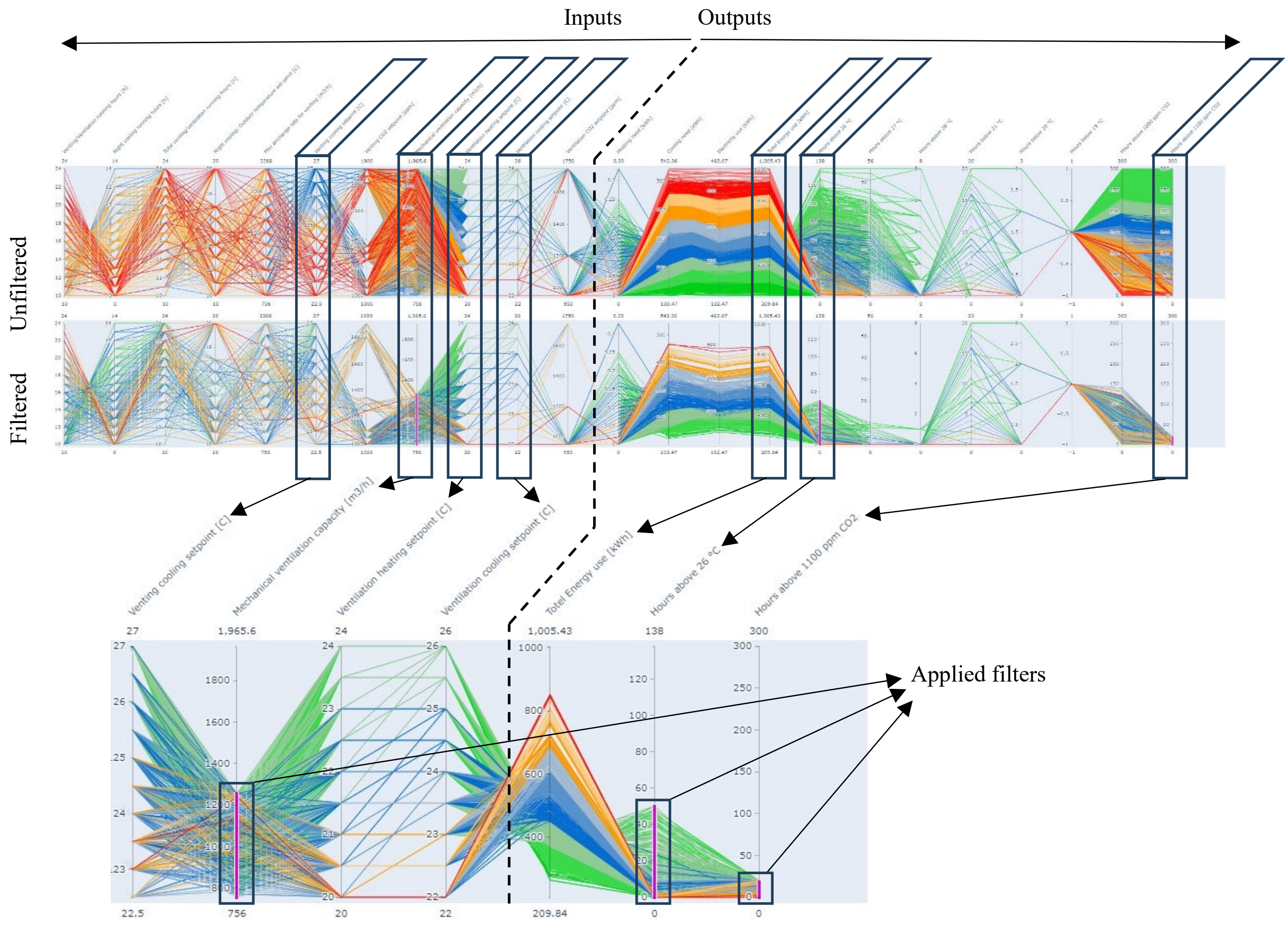

Fig. 2. Parallel coordinate plot for a case study before and after filtering

9.2m*6.5m*2.7 m, with two external walls facing southwest and southeast, as shown in Fig. 3. The occupancy density is 6 m^2/person, and equipment load and lighting load of 25 W/m^2 and 6 W/m^2, respectively. The classroom has window openings on both external façades to facilitate cross-ventilation. At the current stage, the window opening area is regarded as a control variable, which is reflected as the input parameter of natural ventilation capacity. The classroom is also equipped with mechanical ventilation with a heating coil, a cooling coil, and a heat recovery unit. Besides the ventilation system, the room is also equipped with a heating system. It is assumed that the full mixing condition of the air is achieved in the classroom.

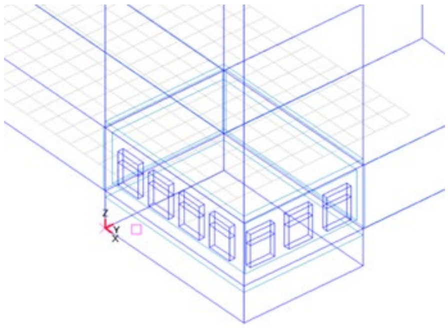

Fig. 3. Building simulation model of the test classroom

Ten control variables are considered in the study, including mechanical ventilation (MV) and natural ventilation (NV) capacities; heating and cooling temperature setpoints; CO_2 setpoints; running hours for ventilation and night cooling. To equally explore possibilities, uniform distributions (discrete and continuous) are assigned to most of the variables and their ranges are described in **Tabe *1***. It must be noted that some of the control variables are correlated, for example, the night cooling running hour is influenced by the ventilation running hour. The same applies to MV and NV cooling setpoints, which depend on MV heating setpoint. The combination of these variables creates an infinitely large control space. To represent this space adequately, 10,000 Monte Carlo simulations are conducted, offering a substantial sample of the overall control possibilities.

The outputs of the study include the energy use (electricity for fan, heating need, cooling need and total energy), thermal comfort (overheating hours and underheating hours) and air quality (hours surpassing CO_2 criteria). It is worth noting that heating and cooling needs presented in the PCP are already converted into electricity consumption by considering their seasonal coefficient of performance. The performance criteria used for the summer case in this study are no hours above 1000 ppm, max 50 hours over 26 °C, no hours lower than 19 °C, and the total energy use is as low as possible. It is also worth noting that only the occupied hours are considered in the thermal comfort and air quality performance criteria.

Considering control variables might have varied impacts on outputs in different seasons, sensitivity analysis is conducted for each season. Only the summer results are presented here, for brevity’s sake. The rank of inputs with respect to their sensitivity towards all outputs (global) and individual outputs (local) are presented in **Table 2**. It is important to notice that apart from the predefined control variables, a randomly sampled dummy input is introduced in the analysis. The dummy has no impact on any of the output, and it is used to identify variables with no impact. The global sensitivity reveals that MV cooling setpoint has the largest sensitivity towards the overall outputs, followed by NV cooling setpoint, MV heating setpoint, and MV capacity, respectively. The NV capacity (max air change rate) ranks lower than the dummy, indicating it has no significant sensitivity towards the outputs. This might be due to the predefined range of the NV air change rate (ACH) being too large, with even the minimum ACH being adequate to maintain acceptable performance. Consequently, increasing the NV capacity shows no notable impact on the system performance. This also indicates that the selection of control variables, along with their ranges and distributions, are critical in the method.

Applying filters based on thermal comfort and air quality criteria narrows our control space to 1463 solutions. By adding the filter on energy consumption, only one control solution remains. The final control solution is shown in the PCP plot in Fig. 4, and the detailed control input and output are described in **Table 3** It is clear that the proposed method is an iterative process which allows the decision makers to observe the correlations between performance criteria and control choices, and provides the flexibility to add and adjust performance criteria at different stages of the project.

The performance of the hybrid ventilation with the final control solution is simulated in BSim, as presented in Fig. 6. MV is activated when occupants are present, lasting several hours after they leave and turning off when the indoor temperature reaches ventilation heating setpoint. The maximum ACH for MV is 5.5 h^{-1}. NV is available during occupied hours but only activated when the temperature or CO_2 level cannot be maintained by MV. However, NV is significantly applied during unoccupied hours to fully explore exploit the night cooling potential, and the maximum ACH for NV is 11.2 h^{-1}.

Table 1. Control variables probability distributions and ranges

Control variables	Unit	Range Min	Range Max	Variable sampling (number of steps)	Distribution Min – Max
Ventilation running hour	h	10	24	Discrete (15)	
Night cooling running hour	h	0	14	Discrete (15)	
Night cooling: Outdoor temperature set-point	°C	10	20	Discrete (9)	
NV capacity	m^3/h (h^{-1})	756 (4.7)	2268 (14)	Discrete (11)	
NV cooling setpoint	°C	22.5	27	Discrete (9)	
NV CO2 setpoint	ppm	1000	1900	Discrete (9)	
MV capacity	m^3/h (h^{-1})	756 (4.7)	1965.6 (12.2)	Continuous	
MV heating setpoint	°C	20	24	Discrete (9)	
MV cooling setpoint	°C	22	26	Discrete (9)	
MV CO2 setpoint	ppm	950	1750	Discrete (3)	

Table 2. Inputs and outputs for the final control solution of the summer case.

Input	Global sensitivity	Local sensitivity											
		Heating need [kWh]	Cooling need [kWh]	Electricity use [kWh]	Total Energy use [kWh]	Hours above 26 °C	Hours above 27 °C	Hours above 28 °C	Hours below 21 °C	Hours below 20 °C	Hours below 19 °C	Hours above 1000 ppm CO2	Hours above 1100 ppm CO2
Ventilation running hours [h]	9	4	8	9	8	7	11	11	4	8	11	9	9
Night cooling running hours [h]	7	1	4	7	6	6	10	8	3	3	6	8	8
Total venting/ventilation running hours [h]	10	7	9	10	10	11	9	9	12	6	5	10	10
Night cooling: Outdoor temperature set-point [ºC]	8	5	5	8	7	5	2	4	7	10	7	7	6
NV capacity [m^3/h]	12	9	12	11	11	10	12	10	8	11	10	11	12
NV cooling setpoint [ºC]	2	11	2	2	2	2	4	5	11	5	3	2	4
NV CO_2 setpoint [ppm]	5	2	6	5	4	8	7	7	2	2	4	3	2
MV capacity [m^3/h]	4	6	10	6	9	3	1	1	6	7	9	6	7
MV heating setpoint [ºC]	3	8	3	3	3	4	5	6	10	12	12	5	5
MV cooling setpoint [ºC]	1	10	1	1	1	1	3	3	9	4	2	1	1
MV CO_2 setpoint [ppm]	6	3	7	5	5	9	8	12	2	9	8	4	3
Dummy	11	12	11	12	12	12	6	2	5	1	1	12	11

Table 3. Inputs and outputs for the final control solution of the summer case.

Input										
Ventilation running hours	Night cooling running hours	Total running hours	Night cooling: Outdoor temperature setpoint	NV capacity	NV cooling setpoint	NV CO_2 setpoint	MV capacity	MV heating setpoint	MV cooling setpoint	MV CO_2 setpoint
h	h	h	°C	m3/h (h^{-1})	°C	ppm	m3/h (h^{-1})	°C	°C	ppm
10	11	21	11	1814 (11.2)	25.5	1000	892 (5.5)	21	25 °C	950 ppm
Output										
Heating need	Cooling need	Electricity use	Total energy use	Hours above 26 °C	Hours above 27 °C	Hours above 28 °C	Hours below 21 °C	Hours below 20 °C	Hours below 19 °C	Hours above 1000 ppm
kWh	kWh	kWh	kWh	hour	hour	hour	hour	hour	hour	hour
0.1	149.7	145.5	295.3	0	0	0	5	0	0	0

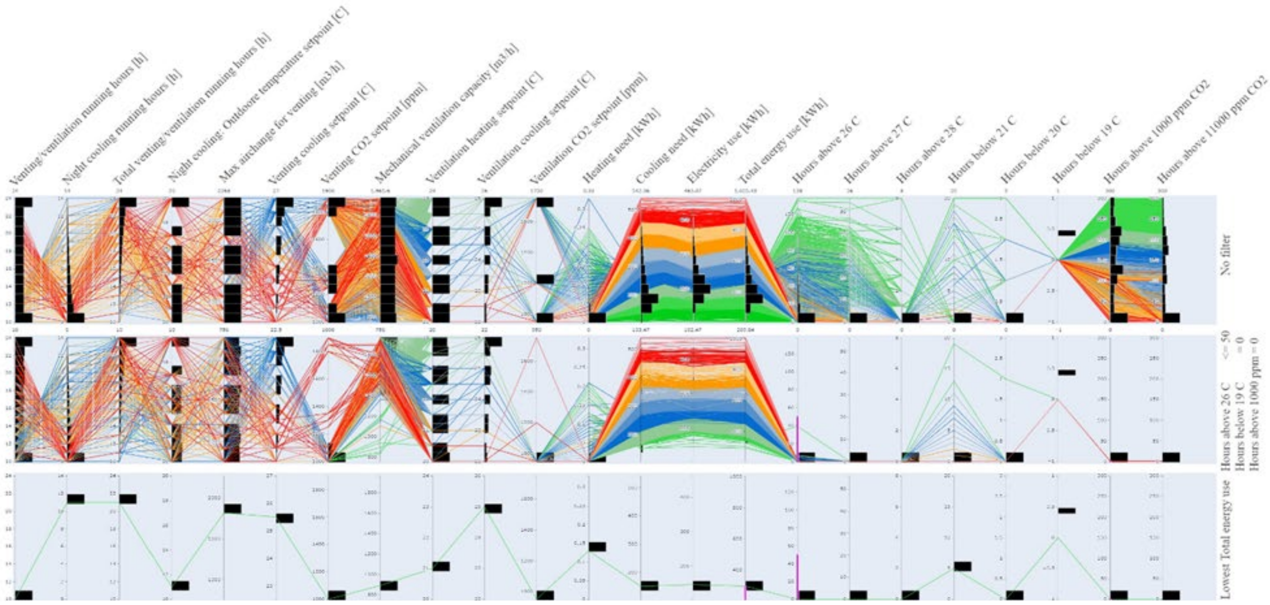

Fig. 4. PCP plot showing the full solution space, the filtered solution space and the final solution.

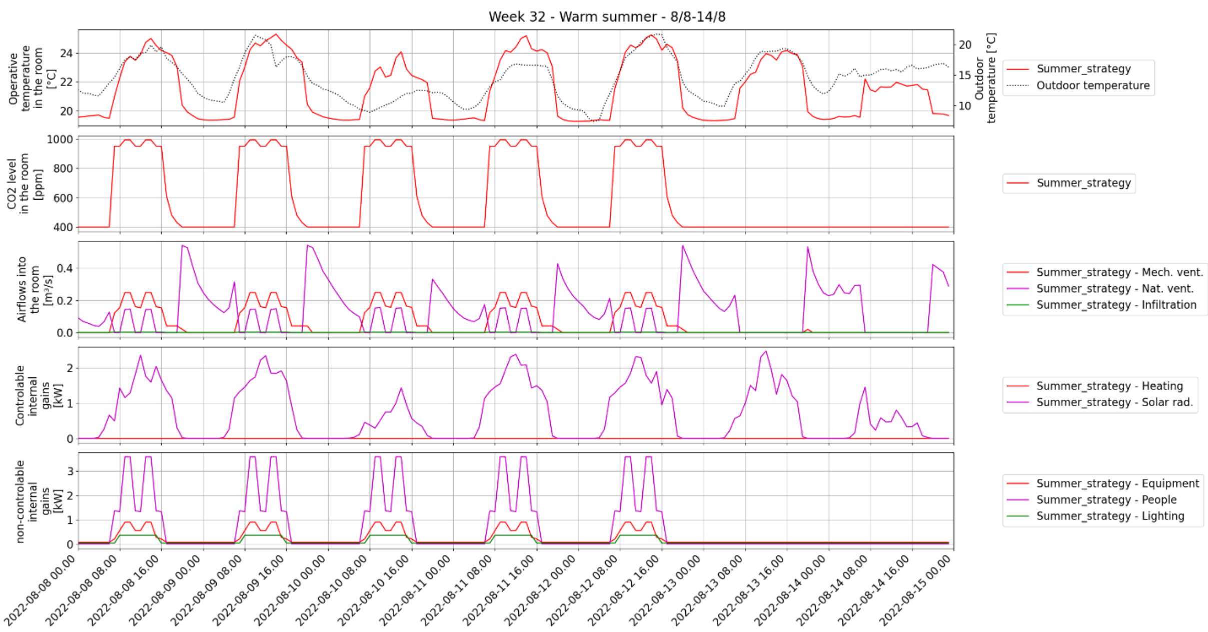

Fig. 5. BSim simulation results in week 32 with the final control solution

4 Conclusions

This study presents a novel Monte Carlo modelling method to facilitate the early-stage development of ventilation control strategies. The method enables exploration of the control space by considering multiple control variables and performance criteria. Through sensitivity analysis, critical control variables are identified, supporting the decision-making process. The proposed method is tested on a typical classroom located in Oslo, which is equipped with a hybrid ventilation system.

The case study revealed the crucial role of selecting control variables and defining their ranges and distributions for the success of this method. Improper selection or definition of input variables will increase the risk of overlooking important variables. Furthermore, the case study demonstrated that the proposed method is an iterative process that allows the decision-makers to observe the correlations between performance criteria and control choices. The method provides flexibility to adjust performance criteria at different stages of the project. This systematical method therefore offers clear advantages over the traditional trial-and-error method.

Further study will investigate the applicability of the proposed method across different ventilation systems, including natural, mechanical and hybrid ventilation. Furthermore, the method will be applied in developing control strategies a demonstration building to validate the applicability in practice.

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