Optimization of night ventilation performance in office buildings in a cold climate

Guo, Rui; Heiselberg, Per; Hu, Yue; Zhang, Chen; Vasilevskis, Sandijs

Published in:
Energy and Buildings

DOI (link to publication from Publisher):
10.1016/j.enbuild.2020.110319

Publication date:
2020

Document Version
Accepted author manuscript, peer reviewed version

Manuscript Details

Manuscript number	ENB_2020_775_R2
Title	Optimization of night ventilation performance in office buildings in a cold climate
Article type	Full Length Article

Abstract

The rising cooling demand and overheating in the building sector, especially in office buildings, have intensified research interest in recent years. Night ventilation (NV) as a passive energy technology has shown a great potential cooling energy and ameliorate indoor thermal environment. In this paper, a holistic approach involving global sensitivity analysis and evolutionary optimization is developed to exclude insignificant parameters and explore optimal NV performance in terms of energy use and thermal comfort. The proposed approach is based on the simulation research of a three-story office building equipped with daytime air conditioning and NV system in a cold climate region. The NV system is equipped with three levels of specific fan power (SFP), representing cases with natural NV and medium and high SFP mechanical NV, respectively. The results show that the activation threshold temperature is not the key parameter for NV performance. Comparing with the case without NV, the three SFP NV systems under a general scheme save 8.8% to 82.5% total cooling energy consumption (TCEC), but increase the average percentage of dissatisfied during occupied hours (aPPD) from 7.5% to about 15%, which may cause overcooling penalty. The optimization decreases the thermal mass area and the night air change rate setpoint at each hour, while increases the minimum indoor air temperature setpoint compared to the general scheme. All three optimal NV schemes significantly improve the indoor thermal comfort by maintaining the aPPD at 7.5%. The optimal medium and high SFP mechanical NV scheme further save 7.1% and 38.6% TCEC compared to the corresponding general mechanical NV scheme, respectively. With a higher SFP, a greater energy saving potential is contributed through NV optimization process. Even though the optimal natural NV scheme consumes more than twice as much TCEC as the general natural NV scheme, it is still worth optimizing the natural NV since the indoor thermal comfort can be improved and the optimal scheme still saves much cooling energy compared to the base case.

Keywords	Night ventilation performance; Global sensitivity analysis; Evolutionary optimization
Taxonomy	Simulation Tool for Optimization, Building Thermal Comfort, Energy Conservation in Building, Energy System Operation
Manuscript category	Passive and Natural Energy and Environmental systems and technologies

Corresponding Author	Rui Guo
Corresponding Author's Institution	Aalborg University
Order of Authors	Rui Guo, Per Heiselberg, Yue Hu, Chen Zhang, Sandijs Vasilevskis
Suggested reviewers	Maria Kolokotroni, Zhengtao Ai, Shady Attia

Submission Files Included in this PDF

File Name [File Type]

Cover letter.docx [Cover Letter]

Detailed response to reviewers.docx [Response to Reviewers]

Revised Manuscript-marked.docx [Revised Manuscript with Changes Marked]

Revised Highlights.docx [Highlights]

Revised Manuscript.docx [Manuscript File]

Conflict of interest statement.docx [Conflict of Interest]

Credit Author Statement.docx [Author Statement]

Declaration of Interest.docx [Supplementary Material]

Research Data Related to this Submission

There are no linked research data sets for this submission. The following reason is given:
Data will be made available on request

To:
Professor Jianlei Niu and Professor Mattheos Santamouris
Editor-in-chief
Energy and Buildings

Dear Editors,

We would like to submit the enclosed manuscript entitled "Optimization of night ventilation performance in office buildings" for your consideration for publication in "*Energy and buildings, VSI: Building Cooling*".

This paper proposes a holistic approach involving global sensitivity analysis and evolutionary optimization is developed to exclude insignificant parameters and explore optimal night ventilation performance in terms of energy use and thermal comfort. The proposed approach is based on the simulation research of a three-story office building equipped with daytime air conditioning and night ventilation system in a city Aarhus, located in a cold climate region. Three types of night ventilation are demonstrated and optimized. The results identify the uninfluential parameter for night ventilation performance and indicate that the optimization of night ventilation is very worth.

We believe that this paper will be of interest to the readership of your journal and the special issue because the quest to make office buildings more energy-efficient and comfortable is currently one of the foremost topics of energy efficiency research. While many researches do not comprehensively consider the complex and non-linear interactions of parameters on the night ventilation performance, the match between the cooling potential of night ventilation and thermal mass activation needs further investigation to save energy use and improve thermal comfort. Optimization of night ventilation performance allows for low building energy consumption and indoor thermal comfort improvement. Any researcher interested in furthering the improvement of the night ventilation performance will find this information very useful.

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare. Please advise if the paper is accepted to the journal and any revision or modification needed!

Thanks and Best Regards!

Rui Guo

Department of the Built Environment

Aalborg University
rgu@build.aau.dk

Dear Editor and Reviewers,

We have revised our manuscript based on your comments. Please find attached the updated version as well as a detailed list of our responses to the comments. We are grateful to you and the valuable suggestions of the reviewers to our paper. As you will see when examining our revision, the reviewer's comments and recommendations have been given consideration and thoroughly addressed in our revised paper. The line, page, equation, and reference numbers from the response part refer to the revised manuscript. We also corrected some of the formation, expression and typing problems. We hope that this manuscript is now acceptable for publication in *Energy and Buildings*. If you have any additional comments and/or concerns, please do not hesitate to contact me directly.

Yours sincerely,

Rui Guo

Reviewer 1:

I appreciate your making clarifications and improvements per recommendations. Thanks for providing a reference for SRRC and explaining it in the detailed response. They were certainly helpful and there is no need to include all explanations in the main text of course, but I think that readers may still benefit from a brief descriptive definition of SRRC in the main text. Without a definition, it is like a black box--with which readers only know that 'the high value means X, a positive sign means Y, a negative sign means Z..." without knowing what it actually is. A simple parenthetical definition would be appreciated right before the supplementary explanations (before lines 213-215).

Below is a couple of examples that might help:

• "The coefficient of determination is the proportion of the variance in the dependent variable that is predictable from the independent variable(s)."

• "The pressure coefficient is a dimensionless number which describes the relative pressures throughout a flow field in fluid dynamics."

They define what those coefficients are. This is fairly minor change, but will greatly help readers demystify the analysis process, as the term is used as a key analysis method in some sections. Thanks for the opportunity to review your great work!

Response: Thanks a lot for your great review and recommendations! We added the following sentence before the explanations of SRRC:

"The SRRC is calculated by performing regression analysis on rank-transformed data (i.e. input parameters and output variables) rather than the raw data."

Reviewer 2:

The authors have satisfactory justified their modelling assumptions by replying to all my comments. However, I believe that some few final clarifications should be added in the manuscript before publication, namely:

1) Response to question 1:

After the sentence added in the manuscript at line 474, the authors should also acknowledge that even applying the optimised ventilation controls (windows opening availability etc), the actual possibility to reach the optimised ACH with natural NV also depends on the architectural design and the location of the building that are excluded in this optimisation analysis (i.e. if the room is single sided or not and if the building is located in urban canyons, where wind speed and pressure is significantly modified by urban geometry).

Response: We appreciated a lot for your detailed advice! We added the following sentence in Section 4:

"It should be noticed that even optimizing the control parameters of a real natural NV may still not fulfill the optimal natural ACH shown in this study. Because the actual possibility to reach the optimal ACH also depends on the architectural design, the building location and local wind environment that were not included in this study."

2) Response to question 2:

The author should elaborate this justification also in the manuscript

Except for these clarifications, the manuscript is suitable for publication in the VSI.

Response: Thanks a lot for your suggestions! We added the following sentence in Section 4:

"Only a single case room was optimized in this study. One reason was that this study devoted to putting forward a method/ability to optimize the NV performance, which was also applicable for multiple rooms or the whole building. Another reason was to reduce the computation time and analyze the optimal results easier and clearer. It is worth noticing that even though the optimal solutions of different rooms or the whole building may differ, the optimal result (i.e. TCEC and aPPD) or trend was also applicable for other cases. As the heat gain of the case room should be much higher than other rooms, but this room still met the overcooling penalty under the high-ACH scenario. Therefore, the same problem will occur in other rooms. Under the same objective and constraint with the omni-optimizer, similar optimal results are expected for other rooms or the whole building."

Optimization of night ventilation performance in office buildings in a cold climate

Rui Guo*, Per Heiselberg, Yue Hu, Chen Zhang, Sandijs Vasilevskis,

Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, DK 9220, Denmark

*corresponding author email address: rgu@build.aau.dk

Optimization of night ventilation performance in office buildings in a cold climate

The rising cooling demand and overheating in the building sector, especially in office buildings, have intensified research interest in recent years. Night ventilation (NV) as a passive energy technology has shown a great potential cooling energy and ameliorate indoor thermal environment. In this paper, a holistic approach involving global sensitivity analysis and evolutionary optimization is developed to exclude insignificant parameters and explore optimal NV performance in terms of energy use and thermal comfort. The proposed approach is based on the simulation research of a three-story office building equipped with daytime air conditioning and NV system in a cold climate region. The NV system is equipped with three levels of specific fan power (SFP), representing cases with natural NV and medium and high SFP mechanical NV, respectively. The results show that the activation threshold temperature is not the key parameter for NV performance. Comparing with the case without NV, the three SFP NV systems under a general scheme save 8.8% to 82.5% total cooling energy consumption (TCEC), but increase the average percentage of dissatisfied during occupied hours (aPPD) from 7.5% to about 15%, which may cause overcooling penalty. The optimization decreases the thermal mass area and the night air change rate setpoint at each hour, while increases the minimum indoor air temperature setpoint compared to the general scheme. All three optimal NV schemes significantly improve the indoor thermal comfort by maintaining the aPPD at 7.5%. The optimal medium and high SFP mechanical NV scheme further save 7.1% and 38.6% TCEC compared to the corresponding general mechanical NV scheme, respectively. With a higher SFP, a greater energy saving potential is contributed through NV optimization process. Even though the optimal natural NV scheme consumes more than twice as much TCEC as the general natural NV scheme, it is still worth optimizing the natural NV since the indoor thermal comfort can be improved and the optimal scheme still saves much cooling energy compared to the base case.

Keywords: Night ventilation performance; Global sensitivity analysis; Evolutionary optimization;

Nomenclature

English symbols

x	Solution vector
n	Number of decision variable
j	Number of inequality constraints
K	Number of equality constraints
g	Vector of inequality constraints
h	Vector of equality constraints
C	Cooling energy consumption for air conditioning or night ventilation

Abbreviations

NV	Night ventilation
AC	Air conditioner or air conditioning
ACH	Air changes per hour
PCM	Phase change material
LHS	Latin hypercube sampling
MCA	Monte Carlo analysis
SHGC	Solar heat gain coefficient
TMY	Typical meteorological year
COP	Coefficient of performance
GA	Genetic algorithm
SRRC	Standardized rank regression coefficient
TCEC	Total cooling energy consumption
PPD	Percentage of dissatisfied
aPPD	Average PPD during occupied hours
SFP	Specific fan power
KKT	Karush–Kuhn–Tucker
NSGA-II	Non-dominated sorting genetic algorithm II

1. Introduction

Cooling demand in buildings, especially in office buildings, is increasing and has become a severe challenge during the last decades [1]. Predictions correspond to an increase in the cooling energy demand of the commercial buildings in 2050, compared to the current consumption, close to 275% [2]. More and more space cooling systems have been installed in office buildings, even in moderate and cold climates such as in Central or Northern Europe [3]. Office buildings usually have high internal heat gains and experience considerable cooling loads due to high solar gains through extensive glazing. While the heating demand can be effectively reduced by installing thermal insulation and improving building airtightness, cooling plays a more significant role in the overall energy demand of buildings [4]. Night ventilation (NV) is a promising way to decrease cooling demand and improve indoor thermal comfort [5]. The basic concept of NV involves cooling the indoor air and the building thermal mass overnight to provide a heat sink available the next day. NV can be driven by natural ventilation, or be supported by hybrid/mechanical ventilation with a mechanical fan [6]. Climatic condition is a key factor to determine the NV efficiency. NV generally has a high cooling potential in moderate or cold climate regions of Central, Eastern, and Northern Europe [3]. However, too much NV in moderate or cold climate regions may overcool the building making people feel cold during occupancy periods or it may consume additional energy for reheating [7].

NV performance is dependent on many parameters. They can be mainly sorted by the cooling capacity of NV and the heat charge/discharge quantity of building thermal mass. The parameters of the cooling capacity of NV involves the night air change rate per hour (ACH), minimum indoor temperature setpoint, night venting duration, and activation threshold temperature (i.e. the temperature difference between indoor and ambient air). Roach et al. [8] optimized the NV temperature setpoint and the ACH in an office building in Adelaide, and concluded that the best NV setpoint temperature is 15 °C and the optimum ACH is 12 h^{-1}. Several NV control strategies for an office building with the daytime active cooling system in northern China were studied and compared [9]. The conclusion was that NV should operate close to the active cooling time with a long ventilation period. The longer the duration of NV operation, the more efficient the NV becomes. Lixia et at. [10] also coupled NV with daytime active cooling to compare the energy-saving potential under 10 ventilation durations for large supermarkets in cold climates in China. Kolokotroni et al. [11] simulated an air-conditioned office building with night cooling and recommended that the night cooling should operate continuously at night until 7:00 when the inside and outside temperatures exceed 18 and 12 °C, respectively. Several researchers have studied efficient control strategies for the cooling capacity of NV. The weather predictive control algorithm was adopted to predict the indoor air temperature during occupancy periods and control the night airflow rate through the heat storage [12][13]. The results seemed positive for reducing the building's cooling demand. Braun et al. [14] developed a simple operation strategy for NV pre-cooling in different buildings in California. They determined that the strategy saved significant compressor energy and that it was cost-effective.

The ability of the building thermal mass to store the excess heat at daytime and to release the heat at night also affects the NV performance [15]. When such charge and discharge process is timed correctly, thermal mass can be utilized to improve thermal comfort and save building energy [16]. The coupling of NV with thermal mass activation has been widely adopted in buildings [17][18][19]. Solgi et al. [20][21] integrated NV with phase change material (PCM) in office buildings in a hot climate region. The amalgamation of NV with PCMs in a building reduced the average indoor temperature, the peak temperature, and saved about 50% of the annual cooling load. Yanbing et al. [22] studied the performance of NV with a novel PCM packed bed storage system in Beijing, China. They found that the system was efficient in cooling down the room temperature and saving the room energy use. Shaviv et al. [23] investigated the NV with the thermal mass. The results showed that it could reduce the indoor temperature by 3–6°C and eliminate the air conditioner (AC) operation in a building with heavy thermal mass in the hot humid climate of Israel. That research shows several shortcomings:

1) The NV performance was evaluated or optimized by a single indicator,

2) The parameters related to NV cooling capacity and thermal mass activation had the coupling effect on the NV performance, which was rarely taken into consideration at the same time, and

3) The related parameter was varied one by one with a few and wide steps (e.g. ACH range from 0 h^{-1} to 12 h^{-1} with a step of 3 h^{-1}) and all the other parameter were fixed to investigate the NV efficiency improvement, which cannot guarantee finding the optimal solution. How the thermal mass activation matches with NV cooling capacity to reach a better performance needs further study.

Simulation-based optimization has become an efficient measure to enhance building performance by satisfying several stringent requirements [24]. Instead of the time-consuming parametric simulation method, different stochastic population-based algorithms (e.g. genetic algorithm, particle swarm optimization, evolutionary algorithm) have been widely used. To maintain a reasonable number of input parameters in the optimization, sensitivity analysis could be conducted to screen out unimportant parameters [24]. The influence of parameters on NV performance has been widely investigated. Artmann et al. [25] did a local sensitivity parameter analysis of NV in an office building and found that the most influential parameters of NV are climate conditions and the air change rate. Kolokotroni et al. [26] did similar work for office buildings in a moderate climate. The results showed that other than air change rates, the most influential parameters also include the thermal mass and internal heat gains. Shaviv et al. [23] investigated the correlation between indoor air temperature and the design parameters for NV in a residential building in a hot humid climate. They found that the air change rate, thermal mass, and daily temperature difference were the most influential parameters. Rui et al. [27] conducted a global sensitivity analysis in an office building under different climatic conditions to identify the most important design parameters of NV. The results showed that the window-wall ratio, thermal mass, internal convective heat transfer coefficient, and night ACH were the most influential parameters. Based on the authors' current literature review, only a few research studies focused on the NV performance improvement by the simulation-based optimization methods.

In summary, due to the complex and non-linear interactions of parameters on the NV performance, a comprehensive consideration is required. Moreover, the one-factor-at-a-time changing method based on a limited distribution of parameters may not be able to find the optimal solution. Few researchers investigated the balance of energy use and indoor thermal comfort when adopting the NV in cold climate regions and the match between the cooling potential of NV and thermal mass activation. This study, therefore, proposes a systematic approach to identify and screen out the uninfluential parameters by using the global sensitivity analysis. Then the key parameters related to the NV performance are optimized with an evolutionary algorithm to minimize the total cooling energy while maintaining the indoor thermal comfort.

2. Methodology

2.1 Research framework

A systematic approach is proposed to quantify the impact of the parameters related to the NV performance on the building energy/thermal performance, and then optimize the identified key parameters, as shown in Figure 1. The approach mainly consists of four steps: 1) generating samples from the distribution of parameters, 2) conducting parametric simulations based on the samples and collecting results, 3) conducting sensitivity analysis to screen out uninfluential parameter based on samples and results, 4) setting the objective and constraint to optimize the key parameters. *In the first step*, samples based on the input parameters are generated by the Latin hypercube sampling (LHS) method with the software SimLab which is designed for Monte Carlo analysis (MCA)–based uncertainty and sensitivity analysis [28] before being sent to the parametric simulation manger jEPlus [29]. *In the second step*, jEplus sends the job list to EnergyPlus [30] to conduct parametric simulation and collects simulation results to transfer back to SimLab. *In the third step*, a global sensitivity analysis based on the regression method is conducted with SimLab to investigate the influences of the parameters and to identify the key parameters for the building energy/thermal performance. *In the last step*, the initial values and distributions of the key parameters as well as the objective function and constraint are set in MOBO [31], a generic freeware written with Java programming language and embedded with several optimization algorithms. Then MOBO generates and sends the input variable based on the omni-optimizer from the parameter distribution to EnergyPlus for simulation before getting the results to determines whether the results fulfill the objective and constraint through the optimization algorithm to find the optimal solutions.

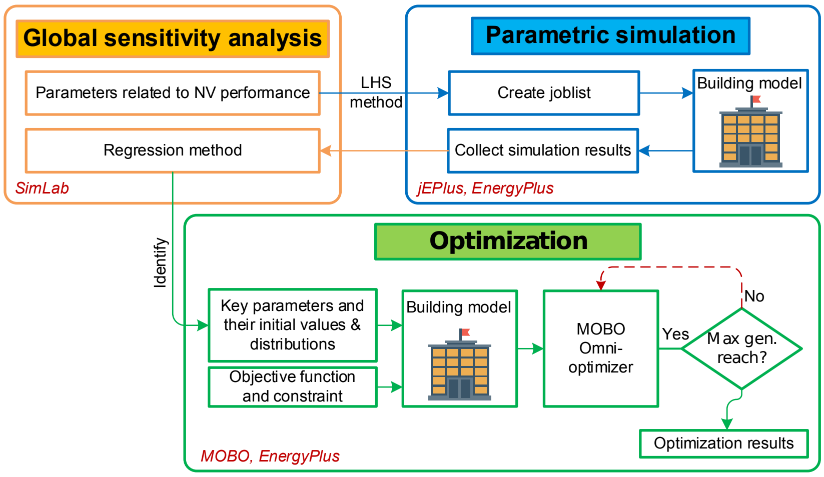

Figure 1. Flow chart of the proposed research framework.

2.2 Baseline model and cooling systems

SketchUp 2015 coupled with EnergyPlus v.8.9 was selected to build the model that originated from an office building in Aarhus Municipality built in 2012, as shown in Figure 2 (A)(B). The building is 103.7 m long and 9.5 m wide, with three stories and a total area of 2924.1 m^2 [32]. Figure 2 (C) shows the layout of the office building. The N, W, S, and C indicate the orientation as north, west, south, and center, respectively, while the number before the orientation abbreviation represents the floor number. An office room (i.e. Zone '1W'), occupied by six persons was selected as the case room. The room floor area is 51.3 m^2, with 2.8 m height. The windows in the case room are the energy-efficient windows with a double pane construction made of 3 mm glass and a 13 mm argon gap. The window U-value is 1.062 W/(m^2·K), while the glass solar heat gain coefficient (SHGC) and visible transmittance are 0.579 and 0.698, respectively. To assume the similar conditions in all adjacent zones, the internal partitions between the case room and adjacent zones were set as adiabatic.

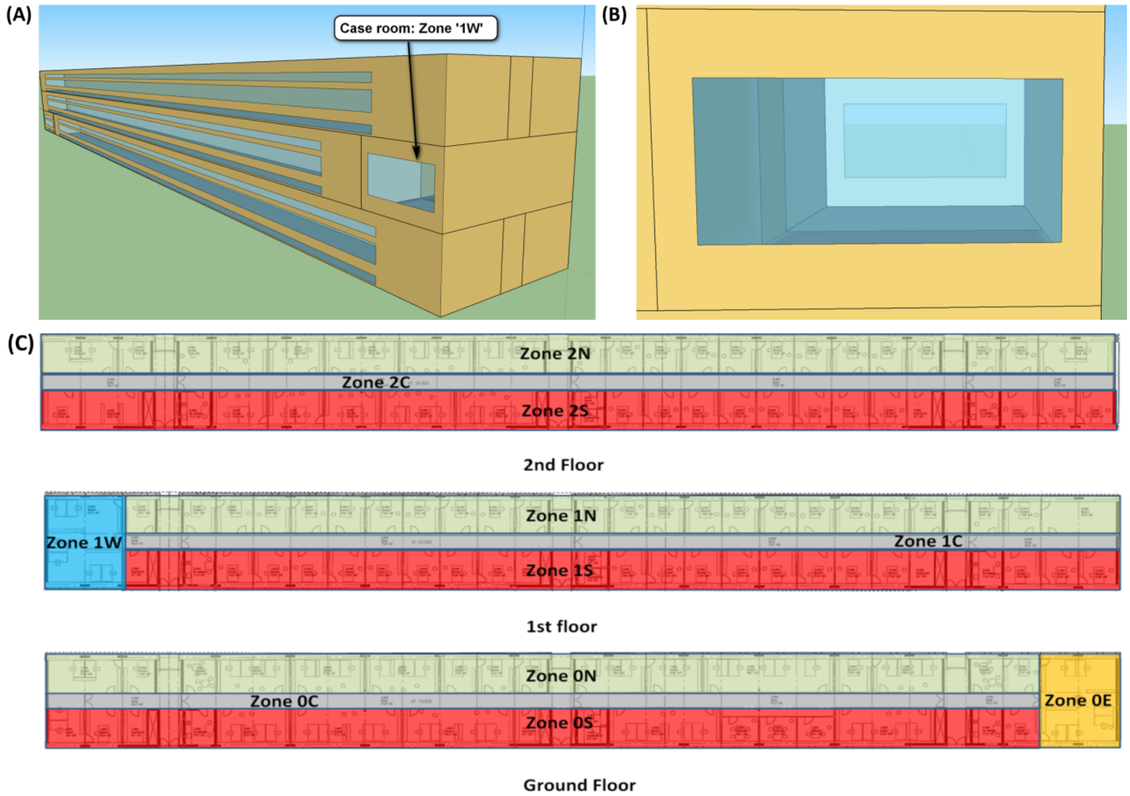

Figure 2. (A)(B) View of the building and case room, (C) layout of the case office building.

Typical meteorological year (TMY) data of Copenhagen, Denmark from the World Meteorological Organization was used in the simulation [33]. The summer season from 1 July to 1 September was chosen in this study. Figure 3 shows the direct solar radiation and outdoor air temperature of Copenhagen in the selected days. The daily mean ambient air temperature oscillated between 10.4 ºC and 21.7 ºC, while the daily maximum value of global horizontal solar irradiance varied between 9.2 W/m^2 and 790.8 W/m^2.

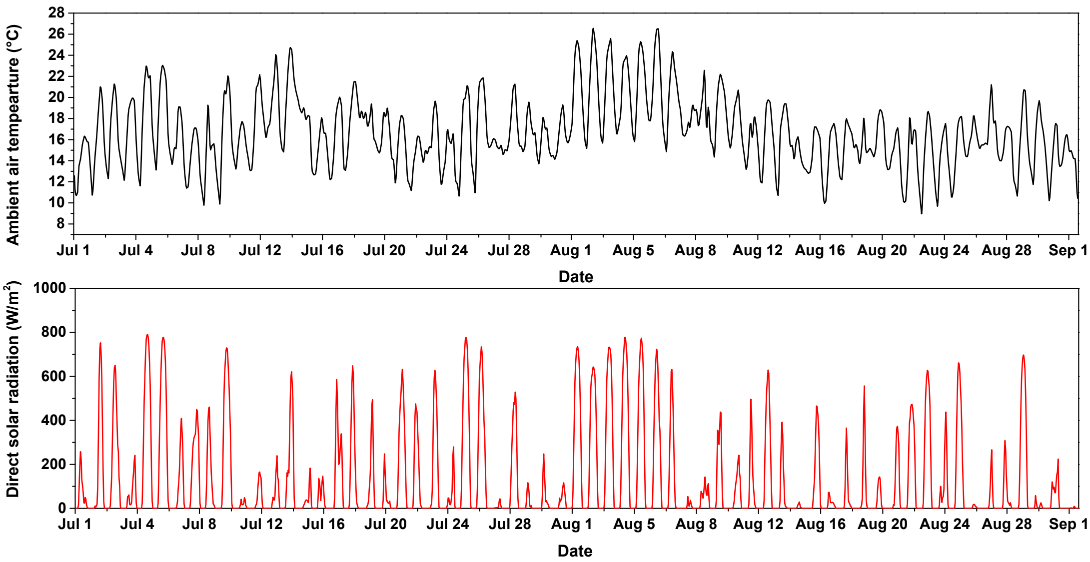

Figure 3. TMY weather data (outdoor temperature and direct solar radiation) of Copenhagen from 1 July to 1 September.

Table 1 shows the detailed thermophysical properties of construction elements. The internal thermal mass area is 20 m^2, while its density is 70 kg/m^2 of the net surface area which fulfills the reasonable range (i.e. 10–100 kg/m^2) for the internal thermal mass density in office buildings [34]. The last column of Table 1 is the total dynamic heat capacity per unit floor area (236.2 kJ/m^2·K), indicating that the case room has a heavy thermal mass level [35]. The dynamic heat capacity c_{dyn} defines how much energy can be stored per area if its surface is exposed to a sinusoidal temperature variation with a 24 h time-period [36].

The internal heat gains were set as people with a load of 120 W/person, lights with 6 W/m^2, and electric equipment with 8 W/m^2 [37]. The hourly operational schedules for the internal heat gains were 1.0 during the occupied hours (08:00-17:00) on weekdays while 0 for other hours. The people's clothing level was set at 0.5 clo in summer [38]. The air change rate of room infiltration was set as 0.5 h^{-1} [39].

Table 1. Thermophysical properties of building materials and detailed composition of the thermal mass.

	d (mm)	ρ (kg/m^3)	c (J/kg/K)	λ (W/m·K)	Total ($kJ/m^2·K$)	c_{dyn}/A_{floor}
External wall						
Plasterboard (fire-resisting)	160	900	1000	0.25		
Concrete 200	200	2385	800	1.2		
PUR 210	210	40	1400	0.021		
Cement plate	15	2000	1500	0.35		
Internal wall						
Gypsum board	25	1000	792	0.4		
Mineral wool	70	1750	1000	0.56		
Gypsum board	25	1000	792	0.4		
Ceiling						
Cast concrete 120	120	1800	1000	1.13	236.2	
Floor						
Linoleum	3	1200	1470	0.17		
Cement screed (fiber reinforced)	50	1400	1000	0.8		
Acoustic insulation	9	556	1700	0.15		
OSB panels	25	600	2150	0.13		
Insulation glass wool	200	28	1030	0.032		
Wooden panels	60	250	2100	0.047		
Internal thermal mass						
Cast concrete 100	100	1800	1000	1.13		

The cooling systems were daytime air conditioning and night ventilation. A packaged terminal air conditioner (AC) with a coefficient of performance (COP) 3.2 and a sizing factor 1.2 from the HVAC Template module of EnergyPlus was set in the case room. The AC temperature setpoint for cooling was set at 24.5 °C, while the outdoor airflow rate was 30 m^3/(h·person) [38]. The AC operated from 08:00-17:00 on weekdays from 1 July to 1 September. The NV system was a balanced system (i.e. a supply fan with an exhaust fan). A general scheme for NV was set as follows. The minimum indoor air temperature setpoint for night ventilation was 18 °C, to cool down the thermal mass efficiently and prevent the overcooling penalty [40]. Besides, the activation threshold temperature was 3 °C (i.e. night cooling only operated when the indoor air temperature exceeded the ambient temperature by 3 °C). The air change rate (ACH) setpoint of night cooling was 10 h^{-1}, which was the specified maximum air change rate [6]. It means that when the activation threshold temperature is met and minimum indoor air temperature is not violated, the fans will operate at the speed equivalent to 10 h^{-1} ACH; otherwise the fans will stop. The night ventilation schedule was during 17:00-08:00 (+1) on weekdays from 1 July to 1 September. The '+1' in the parentheses means the next day. To investigate and optimize the NV performance with different SFPs, three SFPs were chosen which were 0, 0.5 and 1 kW/(m^3/s), representing the natural NV (Case 1), medium SFP mechanical NV (Case 2), and high SFP mechanical NV (Case 3), respectively. The SFPs all fulfilled the recommended 'good-practice' SFP for night cooling should not be higher than 1 kW/(m^3/s) based on the technical note AIVC 65 [41]. Table 2 lists the parameters related to NV.

Table 2. Parameters related to NV.

Parameter		Unit	Case 1	Case 2	Case 3
P1	Night venting duration	h	17:00-08:00	17:00-08:00	17:00-08:00
P2	Minimum indoor temperature setpoint	°C	18	18	18
P3	Night ACH setpoint	h^{-1}	10	10	10
P4	Activation threshold temperature	°C	3	3	3
P5	Internal thermal mass area	m^2	20	20	20
P6	Specific fan power (SFP)	kW/(m^3/s)	0	0.5	1

2.3 Global sensitivity analysis

Global sensitivity analysis methods can investigate the influences of all input parameters on output variables simultaneously, compared to screening methods and local sensitivity methods [42]. This paper adopted the most widely used global sensitivity analysis method, i.e. the regression method, to identify the key parameters related to NV performance on building energy/thermal performance. One reason is that this method is less computationally expensive and easy to understand. Another reason is that this method can avoid the drawbacks of local sensitivity analysis, which only explores a reduced space of the input factor around a base case, does not consider the interaction, and does not have self-verification. Several sensitivity indicators based on the regression method have been used in building energy analysis [27,43–45]. Standardized Rank Regression Coefficient (SRRC) with Monte Carlo analysis (MCA) was selected to quantify the impact of each parameter as it allowed the evaluation for non-linear but monotonic functions among inputs and outputs [45]. The SRRC is calculated by performing regression analysis on rank-transformed data (i.e. input parameters and output variables) rather than the raw data. The larger the absolute value of SRRC, the more influential the input parameter is. SRRC should be used when samples are generated with the LHS method which fully covers the range of each input parameter [46]. The sample size based on LHS was chosen to be 400 as the minimum size should be bigger than 10 times the number of input parameters [45]. SimLab generates the 400 samples based on the aforementioned method before sending them to jEPlus. Then, jEPlus generates building simulation model descriptions (jep file) based on the job list from SimLab to run the EnergyPlus and collects the results (cf. Figure 1). Finally, SimLab gets the results from jEPlus and conducts the sensitivity analysis by calculating the sensitivity measures (i.e. SRRC).

Table 3 shows the range and distribution of the independent parameters related to NV performance. Since the paper aims to quantify the effects of different building design options rather than exploring the possible range of thermal performance for an existing building, the distributions for these parameters should be uniform or discrete [42]. Because there are infinite possible time plans theoretically for night ventilation during 17:00-08:00 (+1), to simply quantify the order and size of the night venting duration, 15 time plans with 1-hour intervals were selected, representing the night venting duration ranging from 1 hour to 15 hours. The upper limit of minimum indoor temperature setpoint was chosen according to the design criteria of thermal conditions in summer in EN 15251 [38]. The upper limit of night ventilation ACH originated from the lowest temperature for cooling in the office room of category III in EN 15251 [38]. The upper limit of SFP was selected according to the technical note AIVC 65 that recommends ‘good-practice’ SFP for night cooling not exceeding 1 kW/(m^3/s) [41]. The total cooling energy consumption (TCEC) which included the energy consumption of AC and NV, and the average predicted percentage of dissatisfied during occupied hours of 08:00-17:00 (aPPD) were selected as the output variables for the evaluation of the building energy and thermal performance.

Table 3. Range and distribution of parameters related to NV performance.

Parameter		Unit	Range
P1	Night venting duration	h	**D** [(17:00-18:00), (17:00-19:00),…, (17:00-08:00)]
P2	Minimum indoor temperature setpoint	℃	**U** [18-22]
P3	Night ACH setpoint	h^{-1}	**U** [0-10]
P4	Activation threshold temperature	℃	**U** [1-3]
P5	Internal thermal mass area	m^2	**U** [0-40]
P6	Specific fan power (SFP)	kW/(m^3/s)	**U** [0-1]

Note: **D**: discrete distribution (levels); **U**: uniform distribution (lower value, upper value).

2.4 Omni-optimizer

This study uses omni-optimizer, an evolutionary optimization algorithm for single and multi-objective optimization that belongs to the category of generational genetic algorithms (GAs). Omni-optimizer originates from a widely used generic NSGA-II (Non-dominated sorting genetic algorithm II) algorithm that finds the Pareto optimal solutions for a multi-objective problem. Furthermore, it has high efficiency of adapting automatically to handle four types of optimization problems: ①Single-objective, uni-optimal; ②Single-objective, multi-optima; ③Multi-objective, uni-optimal optimization; ④Multi-objective, multi-optima optimization [47]. Omni-optimizer also integrates a high-efficiency constraint handling mechanism to process any amount of equality and inequality constraint conditions [48]. The constrained M-objective (M≥1) minimization problem can be posed mathematically as follows:

$$\begin{aligned}
&\text{Minimize} && (f_1(\mathbf{x}),\ f_2(\mathbf{x}),\ldots,f_M(\mathbf{x})),\\
&\text{Subject to} && g_j(\mathbf{x}) \geq 0,\ j = 1, 2,\ldots, J,\\
& && h_k(\mathbf{x}) = 0,\ k = 1, 2,\ldots, K, \qquad (1)\\
& && x_i^{(L)} \leq x_i \leq x_i^{(U)}, i = 1, 2,\ldots,n.
\end{aligned}$$

Where **x** is the solution vector and n is the number of decision variables. j and $g_j(\mathbf{x})$ are the numbers of inequality constraints and their vector, while k and $h_k(\mathbf{x})$ are the number of equality constraints and their vector, respectively. The solution vector **x** that satisfies all aforementioned constraints and variable bounds is regarded as a *feasible* solution. Mathematically, the optimality of a solution depends on a number of KKT (Karush–Kuhn–Tucker) optimality conditions which involve finding the gradients of objective and constraint functions [49]. This study aims at finding the minimum TCEC while maintaining the aPPD within a certain range, which belongs to the type 1 optimization problem as mentioned above.

3. Results and discussion

3.1 NV performance demonstration

Before the global sensitivity analysis and optimization, it is essential to reveal the NV mechanism and demonstrate the NV performance through the simulation. The base case is the building model introduced in Section 2.2 without NV. The NV case 2 (i.e. SFP of 0.5 kW/(m^3/s)) was selected for the NV performance demonstration.

Figure 4 shows the simulated data of zone air temperature, internal thermal mass surface temperature and hourly fan/AC energy consumption of the base case and case 2 in a typical summer day (July 29 to July 30). On the selected night (i.e. 17:00 to 08:00), the ambient air temperature fluctuated between 13.7 ºC to 16.9 ºC, which was very suitable for NV. The zone air and internal thermal mass surface temperatures of the base case varied slightly at night, remaining at about 27.8 ºC and 28.1 ºC, respectively. The reason is that the excess heat stored in the building elements at daytime was released which neutralized the heat loss through the building envelope. Whereas for case 2, due to the fans' operation, the zone air temperature and the internal thermal mass surface temperature were much lower than for the base case at night, and the maximum temperature differences can be 9.3 ºC and 7.4 ºC, respectively. The fan energy consumption at night was 2.7 kWh.

At 08:00 on July 30, the zone air temperatures of the base case and case 2 were 27.8 ºC and 19.4 ºC, respectively. Because the AC setpoint was 24.5 ºC, the AC began to work for the base case at 08:00, while AC was postponed to operate for the base case with NV until 12:45 by about 5 hours. Therefore, for the base case, the zone air temperature began to reach the AC setpoint after 08:00, while the internal thermal mass surface temperature continued to remain steady, presumably due to the energy balance between the heat gain of the internal thermal mass and the heat removed by the AC. However, for case 2, both the temperatures began to go up after 08:00. The zone air temperature rose faster than the internal thermal mass surface temperature and reached to AC setpoint after 12:45, while the surface temperature did not reach AC setpoint until 17:00. This was because the internal thermal mass was mainly heated by convection with room air, and thereby heating was delayed and happened after heating of the air. The AC daily energy consumption for the base case and case 2 was 6.2 kWh and 0.4 kWh, respectively, indicating that NV saved AC energy consumption. When the fan energy consumption at night was taken into consideration, the TCEC for case 2 was 3.1 kWh, which was 3.1 kWh lower than for the base case.

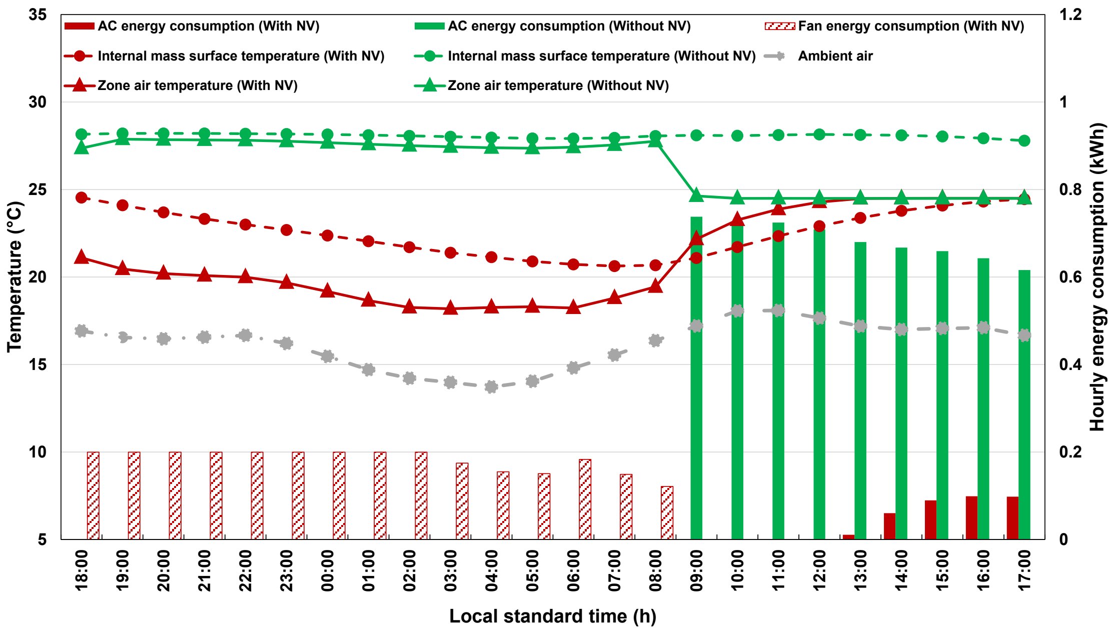

Figure 4. Comparison of zone temperatures and energy consumption of the base case and case 2 with NV in a typical summer day (July 29 to July 30).

Furthermore, the simulated data in Figure 5 shows that the PPD of the base case with NV was always higher than the base case (i.e. without NV), especially at the beginning of the occupied hours. The aPPD for case 2 with NV was 14.1%, 8.7% higher than the base case. The reason was that the NV with high ACH overcooled the indoor air and building elements in the cold climate region, resulting in an overcooling penalty that made people feel cold at the beginning of occupied hours.

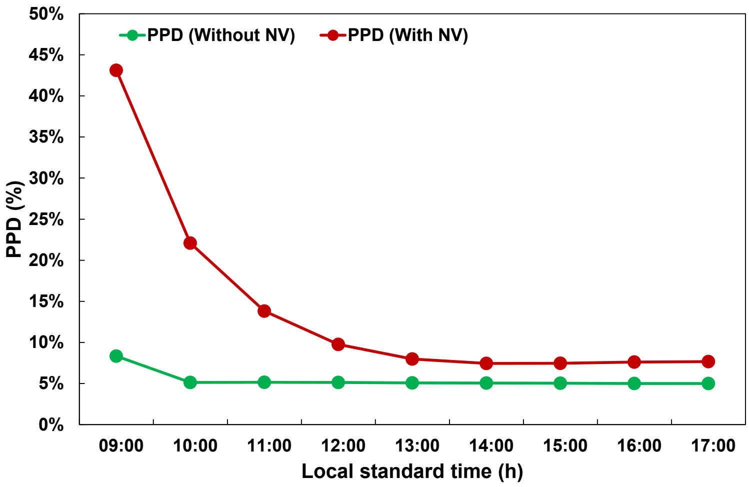

Figure 5. Comparison of PPD of the base case and case 2 at a typical summer daytime (July 30).

3.2 Influence of concerned parameters on building energy/thermal performance

Figure 6 illustrates the influence of the six parameters presented in Table 3 on the TCEC and aPPD (R^2=0.95). A larger absolute value of SRRC means the related parameter is more influential on the corresponding output. Besides, a positive sign of SRRC indicates that the output generally increases as the related input increases, while a negative sign of SRRC means that changes in the input and output tend to go in opposite directions [44]. Night venting duration is the most influential parameter on TCEC, followed by the night ventilation ACH, SFP, and internal thermal mass area. The minimum indoor air temperature setpoint and activation threshold temperature for night cooling activation have little influence on TCEC. The more night cooling (i.e. longer night venting duration and more ACH), the lower TCEC. On the contrary, increasing the SFP and internal thermal mass area tends to consume more TCEC.

For aPPD, night venting duration also has the greatest impact, followed by the internal thermal mass area, night ventilation ACH, and minimum temperature setpoint. The threshold temperature and SFP are not important parameters for the aPPD. Contrary to the impact of night cooling on TCEC, the more night cooling, the more aPPD. It indicates that more night cooling generally contributes to saving more TCEC by postponing or reducing the AC operation, but also results in the overcooling penalty at the beginning of the working day in the cold climate region. Adding the internal thermal mass area tends to reduce the aPPD while increasing the minimum temperature setpoint tends to affect the aPPD inversely. This is presumably because when NV cools a heavy thermal mass level sufficiently, it will remain at a low surface temperature for a longer time during occupied hours, thereby leading to a colder indoor thermal environment. Whereas a higher minimum temperature setpoint can reduce the risk of overcooling phenomena by NV and decrease the aPPD.

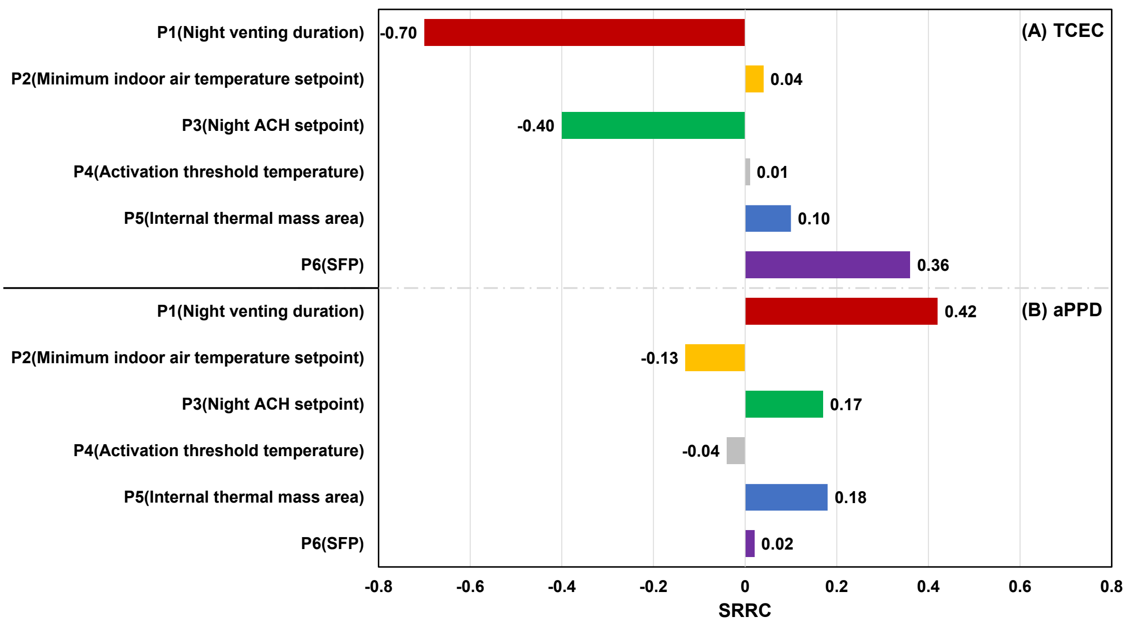

Figure 6. Standardized Rank Regression Coefficient (SRRC) of the concerned parameters.

3.3 Optimization

3.3.1 Optimization setup

The global sensitivity analysis in Section 3.1 manifested that the activation threshold temperature was not a key parameter. Hence, there was no need to optimize it, and it was kept at 3 °C. Besides, the SFP was not optimized as it was an intrinsic parameter once the fan was selected. Cases 1, 2, 3, and base case listed in Table 2 were selected to compare and optimize the NV performance. It is worth noticing that the airflow rate of natural NV is determined/influenced by many factors in real life, like the climate condition, window opening, building orientation, etc. This study focuses on optimizing the airflow rate at night and evaluating the influence of the optimal airflow rate on the building cooling energy and indoor thermal comfort; therefore, how using natural NV can achieve the optimal airflow rate is not an issue in this study. It is also worth noticing that even though the NV is equipped with the variable flow rate fan, it only operates at a constant airflow rate during the entire nighttime under the general scheme when the activation threshold temperature is met and minimum indoor air temperature is not violated. This is due to the lack of indoor air temperature setpoint, which cannot vary the airflow rate. The reason why there is no indoor air temperature setpoint is that the basic concept of NV is to utilize most of the cooling potential of ambient air when office buildings are not occupied.

The optimization aims at finding the optimal night ACH setpoint at each hour. Hence, the variable flow rate fan was selected. According to the technical note AIVC 65 [41], the SFP at each part-load operating point can be estimated as a function of the fraction of maximum flow rate (r) by the following generic equation for $0.2 \leq r \leq 1.0$:

$$\frac{SFP_{part\ load}}{SFP_{max\ load}} \approx a + br + cr^2 + dr^3 \quad (1)$$

Figure 7 illustrates the different levels of the fan performance curve. The ‘Good’ performance curve was selected, which represents systems for which the fan pressure decreases with the airflow rate. The coefficients of *a*, *b*, *c,* and *d* for use in Eq. (1) were 0.5765, -1.5030, 2.6557, and -0.7292 respectively. The maximum SFPs for the medium SFP mechanical NV (Case 2), and high SFP mechanical NV (Case 3) were both at the maximum ACH of 10 h^{-1}. The fraction of maximum flow rate (*r*) at each hour for mechanical NV should be between 0.2 to 1.0 (i.e. ACH of 2 to 10 h^{-1}) or 0 (i.e. stop ventilation). While for natural NV, the fraction *r* was between 0 to 1.0 (i.e. ACH of 0 to 10 h^{-1}) at each hour for optimization.

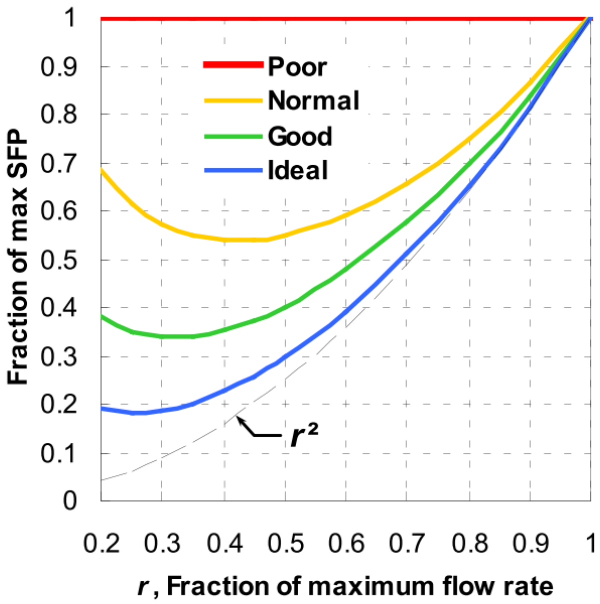

Figure 7. Illustration of Eq. (1) for Poor, Normal, Good, and Ideal systems [41].

To reduce the computational effort and staying close to reality, discrete distributions rather than continuous distributions were selected. Several simplifications and modifications were conducted to improve the simulation and optimization speed:

1) The night ventilation ACH setpoint between 17:00-08:00 (+1) at each 1 hour was optimized with a discrete variable from 0 to 10 h^{-1} with a step of 0.1 h^{-1} for natural NV, while 0 or 2 to 10 h^{-1} with a step of 0.1 h^{-1} for mechanical NV,

2) The internal thermal mass area was optimized with a discrete variable ranging from 0 to 40 m^2 with a step of 0.1 m^2, and

3) The minimum indoor temperature setpoint was optimized with a discrete variable from 18 to 22 ℃ with a step of 0.1 ℃.

Table 5 lists the parameters for cases 1, 2, 3, and base case, while Table 4 summarizes the parameters to be optimized for cases 1, 2, and 3. The population size, maximum generation number, mutation probability, and crossover number, were set as 16, 150, 0.167, and 0.9 respectively by compromising the computational effort and the accuracy [50].

Table 4. Range and distribution of parameters for NV optimization of cases 1, 2, and 3.

Parameter		Unit	Range
O1	Night ventilation ACH setpoint	h^{-1}	**D** [0-10] with step 0.1 h^{-1} at each hour for natural NV **D** 0 or [2-10] with step 0.1 h^{-1} at each hour for mechanical NV
O2	Minimum indoor temperature setpoint	℃	**D** [18-22] with step 0.1 ℃
O3	Internal thermal mass area	m^2	**D** [0-40] with step 0.1 m^2

Note: **D**: discrete distribution (levels);

This study aims at minimizing the TCEC while maintaining the aPPD at a certain range. Furthermore, different constraint levels can be selected, according to the recommended categories of PPD for the design of mechanical cooled buildings in EN 15251 [38]. This study aims at maintaining the same thermal comfort level as in the base case (i.e. the basic building without NV). The simulated aPPD of the base case during the whole simulation period was 7.5%; this was selected as the constraint. Therefore, the optimization problem can be formulated as:

$$\min\ TCEC = C_{AC} + C_{NV} \tag{2}$$

$$\text{subject to} \qquad aPPD < 7.5\% \tag{3}$$

where C_{AC} and C_{NV} stand for the AC energy consumption at daytime and NV energy consumption at night, respectively.

3.3.2 Optimization results

Figure 8 integrates the solutions during the optimization procedure by the omni-optimizer for cases 1, 2, and 3. For the single-objective minimization with the constraint problem, the omni-optimizer utilized the penalty-parameter-less approach to put two solutions in the constrained-tournament selection operator proposed in [51] to determine if a solution is better than the other. The above selection operator fulfilled the following criteria: 1) A feasible solution was always better than an infeasible solution, 2) A feasible solution with better objective function value was preferred to another feasible solution, and 3) An infeasible solution with smaller constraint violation was better than another infeasible solution. Apart from the dominated solutions of three cases, the non-dominated solutions in each case fulfill the Pareto front, which is similar to the multi-objective optimization. It reveals the conflict between the two indicators.

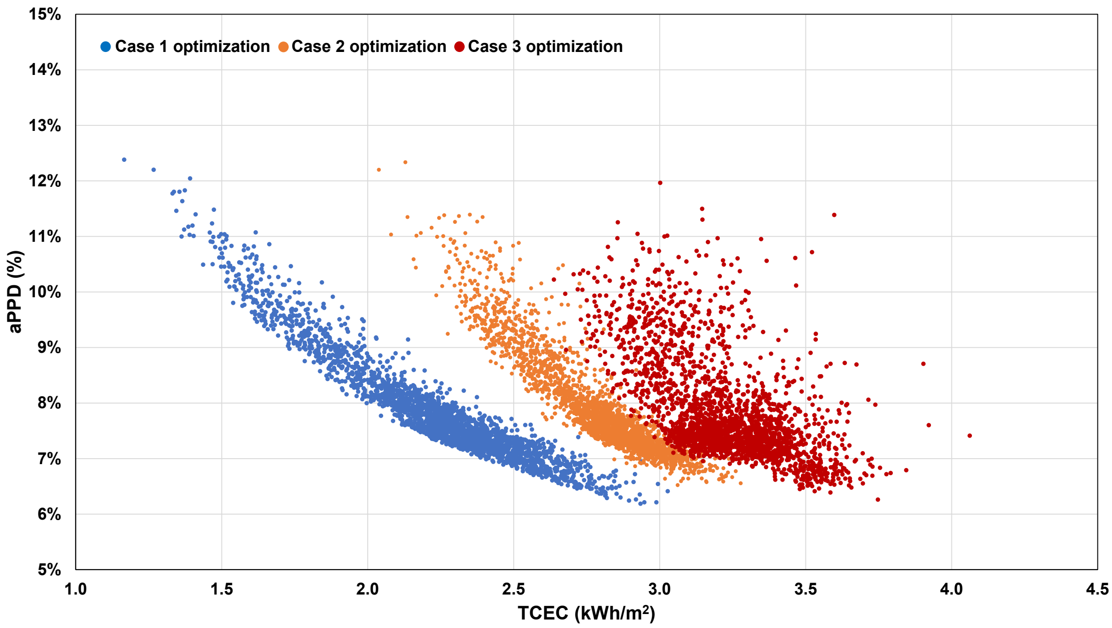

Figure 8. Optimized solutions for cases 1, 2, and 3.

Figure 9 shows the simulated aPPD and TCEC of the research cases. When the base case is equipped with different SFPs NV (i.e. cases 1, 2, 3), the TCEC significantly decreases by 0.5 kWh/m^2 (8.8%) to 4.7 kWh/m^2 (82.5%). Even the high SFP mechanical NV can save 8.8% TCEC compared to the base case. However, adopting NV with a general scheme worsens the indoor thermal comfort by increasing the aPPD from 7.5% to about 15%. After the optimization, all three optimal cases improve the indoor thermal comfort and fulfill the constraint (i.e. aPPD less than 7.5%). The optimal cases 2 and 3 further save 0.4 kWh/m^2 (7.1%) and 2.2 kWh/m^2 (38.6%) TCEC of the cases 2 and 3, respectively. It means that a higher SFP yields a greater total cooling energy saving potential by optimization. Even though the optimal case 1 consumes 1.2 kWh/m^2 more TCEC than case 1, it is still worthy optimizing the natural NV as the overcooling penalty is avoided and the optimal natural NV still saves much TCEC compared to the base case.

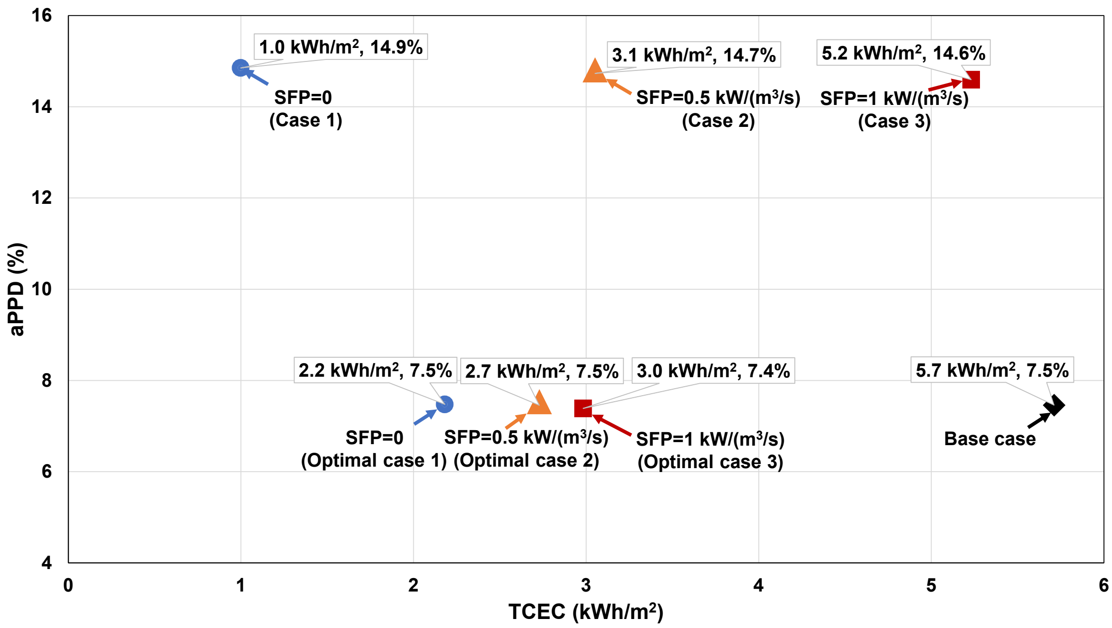

Figure 9. The values of TCEC and aPPD of the research cases.

Figure 10 shows the parameters of the research cases. The area and temperature in the parentheses of the legend are the internal thermal mass area and minimum indoor air temperature setpoint of the corresponding case. The value in the Y-axis represents the night ACH setpoint at each hour. Compared to cases 1, 2, 3, the internal thermal mass areas and night ACH setpoint at each hour of the optimal cases are smaller, but the minimum indoor air temperature setpoints of the optimal cases are higher. The optimal internal thermal mass areas are reduced to 8.7 to 10.4 m^2, which is equivalent to 22.1 to 26.4 $kJ/m^2 \cdot K$ dynamic heat capacity per unit floor area (c_{dyn}/A_{floor}) reduction. The optimal minimum indoor air temperature setpoints vary from 21.2 ºC to 21.6 ºC. The optimal minimum indoor air temperature setpoints are close to the upper limit (i.e. 22 ºC) of this parameter setup, which indicates this setpoint values should not be too low in the cold climate region. There is no big difference between the two optimal parameters mentioned above among the three optimal cases.

However, the optimal night ACH setpoints at each hour during the night are very different from each other. However, all of them are less than 10 h^{-1} of cases 1, 2, and 3. All the optimal cases tend to decrease the night ACH setpoint severely before the occupied hours. Figure 11 illustrates the average night ACH for different cases. The average night ACHs of optimal cases decrease by 4.1 h^{-1} to 5.2 h^{-1}, compared to cases 1, 2, and 3. The average night ACH of optimal case 3 is the lowest among the three optimal cases, while that of the optimal case 1 is the highest. The average night ACHs of cases 1, 2, and 3 are a little different and are not equal to the setpoint of 10 h^{-1}. One reason is that the room inlet air at night can be heated by the intake fan power that will influence the zone air temperature to some extent. In consequence, the case 3 with a higher SFP needs more night cooling. Another reason is that the threshold temperature (i.e. 3 ºC) of NV stops the ventilation when the temperature difference between indoor and outdoor air is not met.

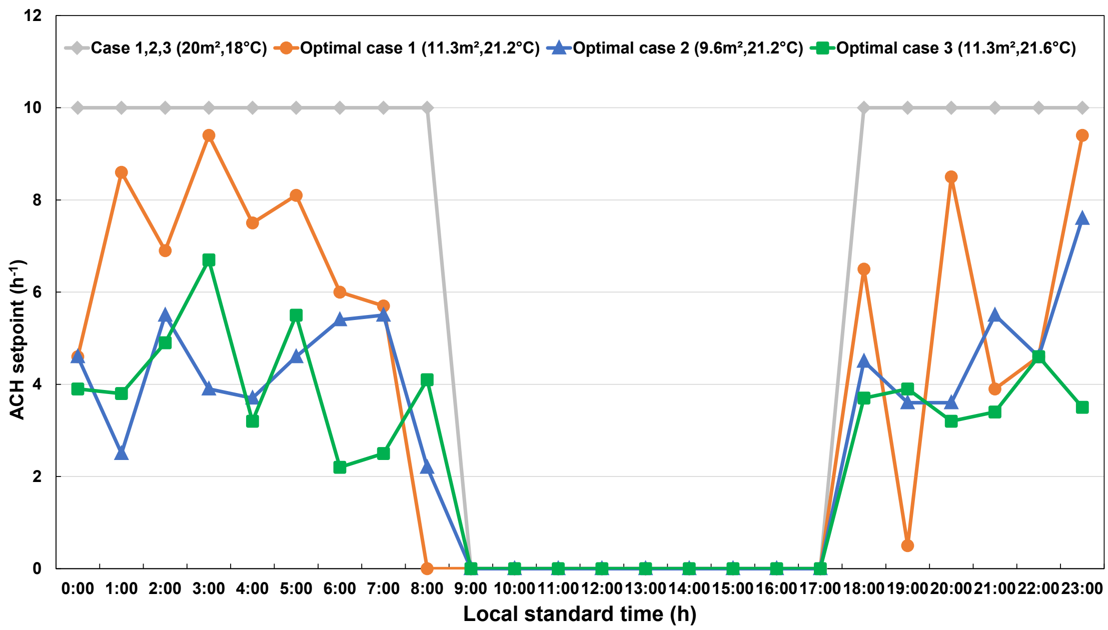

Figure 10. Parameters related to NV of the research cases.

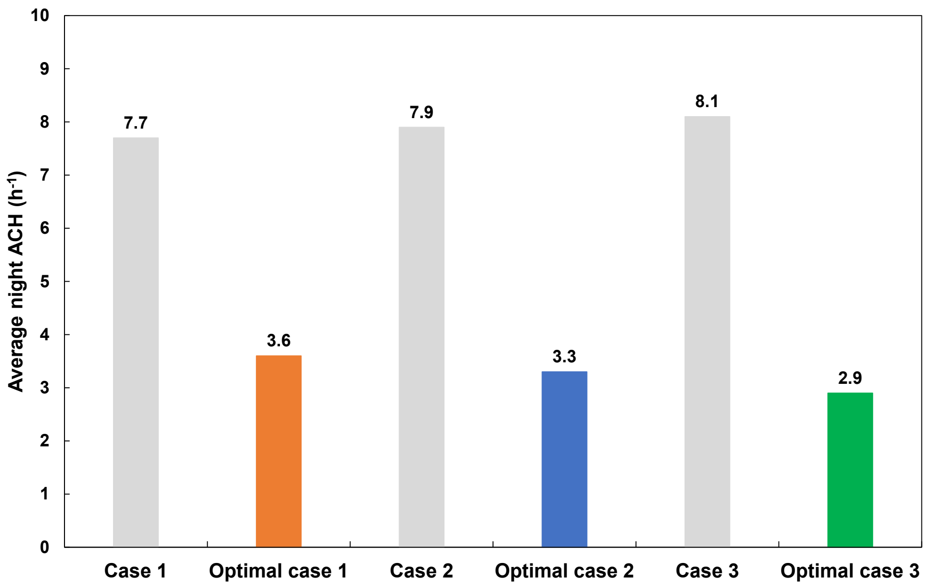

Figure 11. Average night ACH of the research cases.

4. Limitations and prospect

From the authors' perspective, current limitations can be described as follows:

- This study optimized different parameters based on the TMY data, especially the night ACH setpoint at each hour. It may result in the NV performance of certain days under real weather conditions deviating from expectations or not as good as the case adopting the advanced adaptive control algorithm like weather predictive control or model predictive control.
- Natural NV was simplified in this study, which was inherently unstable and highly dependent on the local climate condition, building orientation, window size or window automation system, etc. The expected night ACH for the optimal natural NV may not be fulfilled with the real natural NV system under the real circumstance. However, this study has the potential/ability to optimize the hourly opening availability of windows and ventilation control zone temperature setpoint of a real natural NV system modeled with the AirflowNetwork model in EnergyPlus under the same objective and constraint. It should be noticed that even

optimizing the control parameters of a real natural NV may still not fulfill the optimal natural ACH shown in this study. Because the actual possibility to reach the optimal ACH also depends on the architectural design, the building location, and the local wind environment that were not included in this study.

- Only a single case room was optimized in this study. One reason was that this study devoted to putting forward a method/ability to optimize the NV performance, which was also applicable for multiple rooms or the whole building. Another reason was to reduce the computation time and analyze the optimal results easier and clearer. It is worth noticing that even though the optimal solutions of different rooms or the whole building may differ, the optimal result (i.e. TCEC and aPPD) or trend was also applicable for other cases. As the heat gain of the case room should be much higher than other rooms, but this room still met the overcooling penalty under the high-ACH scenario. Therefore, the same problem will occur in other rooms. Under the same objective and constraint with the omni-optimizer, similar optimal results are expected for other rooms or the whole building.

Overall, the key to obtaining the best NV performance was the match between the cooling potential of NV and the excess heat stored/ released in thermal mass. This study proposed a generic evolutionary algorithm to find that ‘match’ in the approximate infinite combinations, compared to the finite combinations of NV optimization [9][10][52]. Different from the aforementioned advanced control algorithms that generally manipulate a single variable and optimize the building performance based on a given building, this method focused more on guiding engineers or designers at the early building design stage. Furthermore, models identified through the mathematical method from the real building operation data for advanced control algorithms can only maintain the indoor air temperature rather than more precise thermal comfort indicators (e.g. PMV, PPD) within a certain range [53].

Apart from the optimization of the thermal mass amount in this study, the method is also flexible to investigate the optimal parameters related to the excess heat storage and release in the thermal mass; for instance, the insulation level, internal heat gain, thermal mass material (e.g. PCM), daytime cooling methods or related control parameters, etc. As alluded to above, the omni-optimizer has a high efficiency to adapt automatically to handle four types of optimization problems, which can fulfill the different requirements of research and design. The objective or constraint can also be selected based on the research/design purpose. For example, the objective can be to minimize the energy cost based on the real electricity price or utility rate.

5. Conclusion

This study proposes a systematic approach to optimize the NV performance in terms of energy use and thermal comfort. The case study is a three-story office building equipped with daytime air conditioning and an NV system in Aarhus, a city in a cold climate region in Denmark. An NV performance simulation is conducted to demonstrate the NV mechanism. Then, a global sensitivity analysis is carried out to explore the impact of night venting duration, minimum indoor temperature setpoint, night ACH setpoint, activation threshold temperature, and internal thermal mass area and SFP on NV performance. The key design parameters are then optimized based on an evolutionary algorithm to minimize total cooling energy consumption while maintaining the indoor thermal comfort within a reasonable range. Based on the results of the case study, the following conclusions can be made.

- A medium SFP NV with a general scheme can reduce the zone air temperature and internal thermal mass surface temperature by up to 9.3 ºC and 7.4 ºC, respectively on a typical summer day. It can also postpone the air conditioner operation for about 5 hours and save 3.1 kWh TCEC compared to the case without NV. However, by increasing aPPD from 5.1% to 14.1% on the selected day, the NV may overcool the indoor air and building elements to worsen the indoor thermal comfort.

- For TCEC, night venting duration is the most influential parameter, followed by the night ventilation ACH, SFP, and internal thermal mass area. While for aPPD, night venting duration also has the greatest impact, followed by the internal thermal mass area, night ventilation ACH, and minimum temperature setpoint. Activation threshold temperature is an insignificant parameter for NV performance.
- Different SFPs NV under a general scheme saves TCEC by 0.5 kWh/m^2 (8.8%) to 4.7 kWh/m^2 (82.5%) compared to the base case but increases the aPPD from 7.5% to about 15%. After the optimization, all the optimal cases improve the indoor thermal comfort and fulfill the constraint of 7.5%. The optimal medium and high SFP mechanical NV further save 0.4 kWh/m^2 (7.1%) and 2.2 kWh/m^2 (38.6%) TCEC respectively, compared to the corresponding case without optimization. The higher the SFP, the greater the saving potential of TCEC by optimization. Even though the optimal natural NV consumes more than twice as much TCEC as the case without optimization, the natural NV still deserves optimization as the overcooling penalty is avoided and the optimal natural NV still saves more TCEC compared to the case without NV.
- The optimal cases reduce 8.7 to 10.4 m^2 internal thermal mass area compared to the cases without optimization, which is equivalent to 22.1 to 26.4 kJ/m^2·K dynamic heat capacity per unit floor area reduction. The optimization elevates the

minimum indoor air temperature setpoint to 21.2 ºC to 21.6 ºC. There is no much difference between the two optimal parameters mentioned above between the three optimal cases. However, the optimal night ACH setpoints at each hour at night are much different from each other, but both less than 10 h^{-1} of the corresponding case without optimization.

6. Acknowledgment

This work gratefully acknowledges the financial support from the Chinese Scholarship Council (CSC No. 201706050001). The project is carried out as part of IEA EBC Annex 80 Resilient Cooling.

7. Reference

[1] Kolokotroni M, Heiselberg P. Ventilative Cooling: State-of-the-Art Review. Aalborg Univ Aalborg, Denmark 2015.

[2] Santamouris M. Cooling the buildings – past, present and future. Energy Build 2016;128:617–38. doi:10.1016/j.enbuild.2016.07.034.

[3] Artmann N, Manz H, Heiselberg P. Climatic potential for passive cooling of buildings by night-time ventilation in Europe. Appl Energy 2007;84:187–201. doi:10.1016/j.apenergy.2006.05.004.

[4] Santamouris M, Kolokotsa D. Passive cooling dissipation techniques for buildings and other structures: The state of the art. Energy Build 2013;57:74–94. doi:10.1016/j.enbuild.2012.11.002.

[5] Solgi E, Hamedani Z, Fernando R, Skates H, Orji NE. A literature review of night ventilation strategies in buildings. Energy Build 2018;173:337–52. doi:10.1016/j.enbuild.2018.05.052.

[6] O'Donnavan A, Belleri A, Flourentzou F, Zhang G-Q, da Graca GC, Breesch H, et al. Ventilative Cooling Design Guide: Energy in Buildings and Communities Programme. March 2018. Aalborg University, Department of Civil Engineering; 2018.

[7] Liu J, Liu Y, Yang L, Liu T, Zhang C, Dong H. Climatic and seasonal suitability of phase change materials coupled with night ventilation for office buildings in Western China. Renew Energy 2019;147:356–73. doi:10.1016/j.renene.2019.08.069.

[8] Roach P, Bruno F, Belusko M. Modelling the cooling energy of night ventilation and economiser strategies on façade selection of commercial buildings. Energy Build 2013;66:562–70. doi:10.1016/j.enbuild.2013.06.034.

[9] Wang Z, Yi L, Gao F. Night ventilation control strategies in office buildings. Sol Energy 2009;83:1902–13. doi:10.1016/j.solener.2009.07.003.

[10] Wu L-X, Zhao J-N, Wang Z-J. Night ventilation and active cooling coupled operation for large supermarkets in cold climates. Energy Build 2006;38:1409–16. doi:10.1016/J.ENBUILD.2006.02.011.

[11] Kolokotroni M, Aronis A. Cooling-energy reduction in air-conditioned offices by using night ventilation. Appl Energy 1999;63:241–53. doi:10.1016/S0306-2619(99)00031-8.

[12] Vidrih B, Arkar C, Medved S. Generalized model-based predictive weather control for the control of free cooling by enhanced night-time ventilation. Appl Energy 2016;168:482–92. doi:10.1016/j.apenergy.2016.01.109.

[13] Dovrtel K, Medved S. Weather-predicted control of building free cooling system. Appl Energy 2011;88:3088–96. doi:10.1016/j.apenergy.2011.03.010.

[14] Braun JE, Zhong Z. Development and evaluation of a night ventilation precooling algorithm. HVAC R Res 2005;11:433–58. doi:10.1080/10789669.2005.10391147.

[15] Olsthoorn D, Haghighat F, Moreau A, Lacroix G. Abilities and limitations of thermal mass activation for thermal comfort, peak shifting and shaving: A review. Build Environ 2017;118:113–27. doi:10.1016/J.BUILDENV.2017.03.029.

[16] Farid MM, Khudhair AM, Razack SAK, Al-Hallaj S. A review on phase change energy storage: Materials and applications. Energy Convers Manag 2004. doi:10.1016/j.enconman.2003.09.015.

[17] Souayfane F, Fardoun F, Biwole PH. Phase change materials (PCM) for cooling

applications in buildings: A review. Energy Build 2016;129:396–431. doi:10.1016/j.enbuild.2016.04.006.

[18] Akeiber H, Nejat P, Majid MZA, Wahid MA, Jomehzadeh F, Zeynali Famileh I, et al. A review on phase change material (PCM) for sustainable passive cooling in building envelopes. Renew Sustain Energy Rev 2016;60:1470–97. doi:10.1016/j.rser.2016.03.036.

[19] Pomianowski M, Heiselberg P, Zhang Y. Review of thermal energy storage technologies based on PCM application in buildings. Energy Build 2013;67:56–69. doi:10.1016/j.enbuild.2013.08.006.

[20] Solgi E, Fayaz R, Kari BM. Cooling load reduction in office buildings of hot-arid climate, combining phase change materials and night purge ventilation. Renew Energy 2016;85:725–31. doi:10.1016/j.renene.2015.07.028.

[21] Solgi E, Kari BM, Fayaz R, Taheri H. The impact of phase change materials assisted night purge ventilation on the indoor thermal conditions of office buildings in hot-arid climates. Energy Build 2017;150:488–97. doi:10.1016/j.enbuild.2017.06.035.

[22] Yanbing K, Yi J, Yinping Z. Modeling and experimental study on an innovative passive cooling system - NVP system. Energy Build 2003. doi:10.1016/S0378-7788(02)00141-X.

[23] Shaviv E, Yezioro A, Capeluto IG. Thermal mass and night ventilation as passive cooling design strategy. Renew Energy 2001;24:445–52. doi:10.1016/S0960-1481(01)00027-1.

[24] Nguyen AT, Reiter S, Rigo P. A review on simulation-based optimization methods applied to building performance analysis. Appl Energy 2014;113:1043–58. doi:10.1016/j.apenergy.2013.08.061.

[25] Artmann N, Manz H, Heiselberg P. Parameter study on performance of building cooling by night-time ventilation. Renew Energy 2008;33:2589–98. doi:10.1016/j.renene.2008.02.025.

[26] Kolokotroni M, Webb BC, Hayes SD. Summer cooling with night ventilation for office buildings in moderate climates. Energy Build 1998;27:231–7. doi:10.1016/s0378-7788(97)00048-0.

[27] Guo R, Hu Y, Liu M, Heiselberg P. Influence of design parameters on the night ventilation performance in office buildings based on sensitivity analysis. Sustain Cities Soc 2019;50:101661. doi:10.1016/j.scs.2019.101661.

[28] EU Science Hub. SimLab v2.2 2008.

[29] Zhang Y, Korolija I. jEPlus-An EnergyPlus simulation manager for parametrics 2016.

[30] Department of Energy U. EnergyPlus, Simulation Program v8.9 2017. https://energyplus.net/documentation.

[31] Palonen M, Hamdy M, Hasan A. Mobo a new software for multi-objective building performance optimization. Proc. BS 2013 13th Conf. Int. Build. Perform. Simul. Assoc., 2013, p. 2567–74.

[32] Liu M, Heiselberg P. Energy flexibility of a nearly zero-energy building with weather predictive control on a convective building energy system and evaluated with different metrics. Appl Energy 2019;233–234:764–75. doi:10.1016/j.apenergy.2018.10.070.

[33] WMO Country Profile Database. World Meteorological Organization 2018. https://www.wmo.int/cpdb/.

[34] Johra H, Heiselberg P. Influence of internal thermal mass on the indoor thermal dynamics and integration of phase change materials in furniture for building energy storage: A review. Renew Sustain Energy Rev 2017;69:19–32. doi:10.1016/j.rser.2016.11.145.

[35] ISO EN. 13790: Energy performance of buildings–Calculation of energy use for space heating and cooling (EN ISO 13790: 2008). Eur Comm Stand (CEN), Brussels 2008.

[36] EN ISO 13786. Thermal performance of building components – Dynamic thermal characteristics – Calculation methods 2017.

[37] Guo R, Hu Y, Liu M, Heiselberg P. Optimal Night Mechanical Ventilation control strategy in office buildings. IOP Conf. Ser. Mater. Sci. Eng., vol. 609, IOP Publishing; 2019, p. 032013. doi:10.1088/1757-899X/609/3/032013.

[38] EN 15251. Indoor environmental input parameters for design and assessment of

energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics 2007.

[39] EN 16798-3. Energy performance of buildings – Ventilation for buildings – Part 3: For non-residential buildings – Performance requirements for ventilation and room-conditioning systems (Modules M5-1, M5-4) 2017.

[40] J MA. Control of natural ventilation. 1995.

[41] International Energy Agency. Technical note AIVC 65 - Recommendations on specific fan power and fan system efficiency. 2009.

[42] Wei T. A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 2013;20:411–9. doi:10.1016/j.rser.2012.12.014.

[43] Lim H, Zhai Z (John). Influences of energy data on Bayesian calibration of building energy model. Appl Energy 2018;231:686–98. doi:10.1016/j.apenergy.2018.09.156.

[44] Yildiz Y, Korkmaz K, Göksal özbalta T, Durmus Arsan Z. An approach for developing sensitive design parameter guidelines to reduce the energy requirements of low-rise apartment buildings. Appl Energy 2012;93:337–47. doi:10.1016/j.apenergy.2011.12.048.

[45] European Commission - IPSC. Simlab 2.2: Reference Manual 2008.

[46] Helton JC, Davis FJ. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. Reliab Eng Syst Saf 2003. doi:10.1016/S0951-8320(03)00058-9.

[47] Deb K, Tiwari S. Omni-optimizer: A generic evolutionary algorithm for single and multi-objective optimization. Eur J Oper Res 2008;185:1062–87. doi:10.1016/j.ejor.2006.06.042.

[48] Wang L, Wu J, Wang T, Han R. An optimization method based on random fork tree coding for the electrical networks of offshore wind farms. Renew Energy 2020;147:1340–51. doi:10.1016/j.renene.2019.09.100.

[49] Deb K. Optimization for engineering design: Algorithms and examples. PHI Learning Pvt. Ltd.; 2012.

[50] Palonen M, Hasan A. MOBO Beta 0.3 b Maunal Version 1.4 2014.

[51] Deb K. An efficient constraint handling method for genetic algorithms. Comput Methods Appl Mech Eng 2000. doi:10.1016/S0045-7825(99)00389-8.

[52] Ran J, Tang M. Passive cooling of the green roofs combined with night-time ventilation and walls insulation in hot and humid regions. Sustain Cities Soc 2018;38:466–75. doi:10.1016/j.scs.2018.01.027.

[53] Thieblemont H, Haghighat F, Ooka R, Moreau A. Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the art. Energy Build 2017;153:485–500. doi:10.1016/j.enbuild.2017.08.010.

Highlights

- The parameters related to NV performance are identified and optimized.
- Activation threshold temperature is not the key parameter for NV performance.
- A general NV saves up to 82.5% energy but may cause overcooling penalty.
- NV optimization improves thermal comfort and further saves up to 38.6% energy.
- Optimization of natural NV improves the thermal comfort although it consumes more energy.

Optimization of night ventilation performance in office buildings in a cold climate

Rui Guo*, Per Heiselberg, Yue Hu, Chen Zhang, Sandijs Vasilevskis,

Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, DK 9220, Denmark

*corresponding author email address: rgu@build.aau.dk

Optimization of night ventilation performance in office buildings in a cold climate

The rising cooling demand and overheating in the building sector, especially in office buildings, have intensified research interest in recent years. Night ventilation (NV) as a passive energy technology has shown a great potential cooling energy and ameliorate indoor thermal environment. In this paper, a holistic approach involving global sensitivity analysis and evolutionary optimization is developed to exclude insignificant parameters and explore optimal NV performance in terms of energy use and thermal comfort. The proposed approach is based on the simulation research of a three-story office building equipped with daytime air conditioning and NV system in a cold climate region. The NV system is equipped with three levels of specific fan power (SFP), representing cases with natural NV and medium and high SFP mechanical NV, respectively. The results show that the activation threshold temperature is not the key parameter for NV performance. Comparing with the case without NV, the three SFP NV systems under a general scheme save 8.8% to 82.5% total cooling energy consumption (TCEC), but increase the average percentage of dissatisfied during occupied hours (aPPD) from 7.5% to about 15%, which may cause overcooling penalty. The optimization decreases the thermal mass area and the night air change rate setpoint at each hour, while increases the minimum indoor air temperature setpoint compared to the general scheme. All three optimal NV schemes significantly improve the indoor thermal comfort by maintaining the aPPD at 7.5%. The optimal medium and high SFP mechanical NV scheme further save 7.1% and 38.6% TCEC compared to the corresponding general mechanical NV scheme, respectively. With a higher SFP, a greater energy saving potential is contributed through NV optimization process. Even though the optimal natural NV scheme consumes more than twice as much TCEC as the general natural NV scheme, it is still worth optimizing the natural NV since the indoor thermal comfort can be improved and the optimal scheme still saves much cooling energy compared to the base case.

Keywords: Night ventilation performance; Global sensitivity analysis; Evolutionary optimization;

Nomenclature

English symbols

x	Solution vector
n	Number of decision variable
j	Number of inequality constraints
K	Number of equality constraints
g	Vector of inequality constraints
h	Vector of equality constraints
C	Cooling energy consumption for air conditioning or night ventilation

Abbreviations

NV	Night ventilation
AC	Air conditioner or air conditioning
ACH	Air changes per hour
PCM	Phase change material
LHS	Latin hypercube sampling
MCA	Monte Carlo analysis
SHGC	Solar heat gain coefficient
TMY	Typical meteorological year
COP	Coefficient of performance
GA	Genetic algorithm
SRRC	Standardized rank regression coefficient
TCEC	Total cooling energy consumption
PPD	Percentage of dissatisfied
aPPD	Average PPD during occupied hours
SFP	Specific fan power
KKT	Karush–Kuhn–Tucker
NSGA-II	Non-dominated sorting genetic algorithm II

1. Introduction

Cooling demand in buildings, especially in office buildings, is increasing and has become a severe challenge during the last decades [1]. Predictions correspond to an increase in the cooling energy demand of the commercial buildings in 2050, compared to the current consumption, close to 275% [2]. More and more space cooling systems have been installed in office buildings, even in moderate and cold climates such as in Central or Northern Europe [3]. Office buildings usually have high internal heat gains and experience considerable cooling loads due to high solar gains through extensive glazing. While the heating demand can be effectively reduced by installing thermal insulation and improving building airtightness, cooling plays a more significant role in the overall energy demand of buildings [4]. Night ventilation (NV) is a promising way to decrease cooling demand and improve indoor thermal comfort [5]. The basic concept of NV involves cooling the indoor air and the building thermal mass overnight to provide a heat sink available the next day. NV can be driven by natural ventilation, or be supported by hybrid/mechanical ventilation with a mechanical fan [6]. Climatic condition is a key factor to determine the NV efficiency. NV generally has a high cooling potential in moderate or cold climate regions of Central, Eastern, and Northern Europe [3]. However, too much NV in moderate or cold climate regions may overcool the building making people feel cold during occupancy periods or it may consume additional energy for reheating [7].

NV performance is dependent on many parameters. They can be mainly sorted by the cooling capacity of NV and the heat charge/discharge quantity of building thermal mass. The parameters of the cooling capacity of NV involves the night air change rate per hour (ACH), minimum indoor temperature setpoint, night venting duration, and activation threshold temperature (i.e. the temperature difference between indoor and ambient air). Roach et al. [8] optimized the NV temperature setpoint and the ACH in an office building in Adelaide and concluded that the best NV setpoint temperature is 15 °C and the optimum ACH is 12 h^{-1}. Several NV control strategies for an office building with the daytime active cooling system in northern China were studied and compared [9]. The conclusion was that NV should operate close to the active cooling time with a long ventilation period. The longer the duration of NV operation, the more efficient the NV becomes. Lixia et at. [10] also coupled NV with daytime active cooling to compare the energy-saving potential under 10 ventilation durations for supermarkets in cold climates in China. Kolokotroni et al. [11] simulated an air-conditioned office building with night cooling and recommended that the night cooling should operate continuously at night until 7:00 when the inside and outside temperatures exceed 18 and 12 °C, respectively. Several researchers have studied efficient control strategies for the cooling capacity of NV. The weather predictive control algorithm was adopted to predict the indoor air temperature during occupancy periods and control the night airflow rate through the heat storage [12][13]. The results seemed positive for reducing the building's cooling demand. Braun et al. [14] developed a simple operation strategy for NV pre-cooling in different buildings in California. They determined that the strategy saved significant compressor energy and that it was cost-effective.

The ability of the building thermal mass to store the excess heat at daytime and to release the heat at night also affects the NV performance [15]. When such the charge and discharge process is timed correctly, thermal mass can be utilized to improve thermal comfort and save building energy [16]. The coupling of NV with thermal mass activation has been widely adopted in buildings [17][18][19]. Solgi et al. [20][21] integrated NV with phase change material (PCM) in office buildings in a hot climate region. The amalgamation of NV with PCMs in a building reduced the average indoor temperature, the peak temperature, and saved about 50% of the annual cooling load. Yanbing et al. [22] studied the performance of NV with a novel PCM packed bed storage system in Beijing, China. They found that the system was efficient in cooling down the room temperature and saving the room energy use. Shaviv et al. [23] investigated the NV with the thermal mass. The results showed that it could reduce the indoor temperature by 3–6°C and eliminate the air conditioner (AC) operation in a building with heavy thermal mass in the hot humid climate of Israel. That research shows several shortcomings:

1) The NV performance was evaluated or optimized by a single indicator,

2) The parameters related to NV cooling capacity and thermal mass activation had the coupling effect on the NV performance, which was rarely taken into consideration at the same time, and

3) The related parameter was varied one by one with a few and wide steps (e.g. ACH range from 0 h^{-1} to 12 h^{-1} with a step of 3 h^{-1}) and all the other parameters were fixed to investigate the NV efficiency improvement, which cannot guarantee to find the optimal solution. How the thermal mass activation matches with NV cooling capacity to reach a better performance needs further study.

Simulation-based optimization has become an efficient measure to enhance building performance by satisfying several stringent requirements [24]. Instead of the time-consuming parametric simulation method, different stochastic population-based algorithms (e.g. genetic algorithm, particle swarm optimization, evolutionary algorithm) have been widely used. To maintain a reasonable number of input parameters in the optimization, sensitivity analysis could be conducted to screen out unimportant parameters [24]. The influence of parameters on NV performance has been widely investigated. Artmann et al. [25] did a local sensitivity parameter analysis of NV in an office building and found that the most influential parameters of NV are climate conditions and the air change rate. Kolokotroni et al. [26] did similar work for office buildings in a moderate climate. The results showed that other than air change rates, the most influential parameters also include the thermal mass and internal heat gains. Shaviv et al. [23] investigated the correlation between indoor air temperature and the design parameters for NV in a residential building in a hot humid climate. They found that the air change rate, thermal mass, and daily temperature difference were the most influential parameters. Rui et al. [27] conducted a global sensitivity analysis in an office building under different climatic conditions to identify the most important design parameters of NV. The results showed that the window-wall ratio, thermal mass, internal convective heat transfer coefficient, and night ACH were the most influential parameters. Based on the authors' current literature review, only a few research studies focused on the NV performance improvement by the simulation-based optimization methods.

In summary, due to the complex and non-linear interactions of parameters on the NV performance, a comprehensive consideration is required. Moreover, the one-factor-at-a-time changing method based on a limited distribution of parameters may not be able to find the optimal solution. Few researchers investigated the balance of energy use and indoor thermal comfort when adopting the NV in cold climate regions and the match between the cooling potential of NV and thermal mass activation. This study, therefore, proposes a systematic approach to identify and screen out the uninfluential parameters by using the global sensitivity analysis. Then the key parameters related to the NV performance are optimized with an evolutionary algorithm to minimize the total cooling energy while maintaining the indoor thermal comfort.

2. Methodology

2.1 Research framework

A systematic approach is proposed to quantify the impact of the parameters related to the NV performance on the building energy/thermal performance, and then optimize the identified key parameters, as shown in Figure 1. The approach mainly consists of four steps: 1) generating samples from the distribution of parameters, 2) conducting parametric simulations based on the samples and collecting results, 3) conducting sensitivity analysis to screen out uninfluential parameter based on samples and results, 4) setting the objective and constraint to optimize the key parameters. *In the first step*, samples based on the input parameters are generated by the Latin hypercube sampling (LHS) method with the software SimLab which is designed for Monte Carlo analysis (MCA)–based uncertainty and sensitivity analysis [28] before being sent to the parametric simulation manger jEPlus [29]. *In the second step*, jEplus sends the job list to EnergyPlus [30] to conduct parametric simulation and collects simulation results to transfer back to SimLab. *In the third step*, a global sensitivity analysis based on the regression method is conducted with SimLab to investigate the influences of the parameters and to identify the key parameters for the building energy/thermal performance. *In the last step*, the initial values and distributions of the key parameters as well as the objective function and constraint are set in MOBO [31], a generic freeware written with Java programming language and embedded with several optimization algorithms. Then MOBO generates and sends the input variable based on the omni-optimizer from the parameter distribution to EnergyPlus for simulation before getting the results to determines whether the results fulfill the objective and constraint through the optimization algorithm to find the optimal solutions.

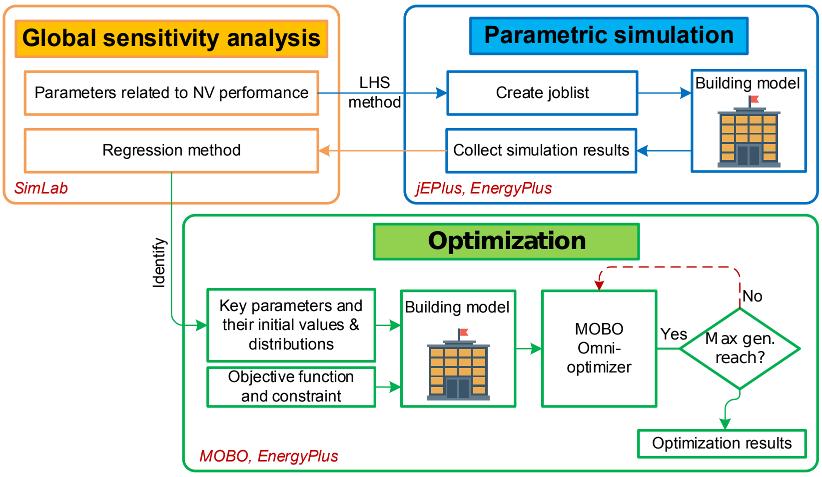

Figure 1. Flow chart of the proposed research framework.

2.2 Baseline model and cooling systems

SketchUp 2015 coupled with EnergyPlus v.8.9 was selected to build the model that originated from an office building in Aarhus Municipality built in 2012, as shown in Figure 2 (A)(B). The building is 103.7 m long and 9.5 m wide, with three stories and a total area of 2924.1 m^2 [32]. Figure 2 (C) shows the layout of the office building. The N, W, S, and C indicate the orientation as north, west, south, and center, respectively, while the number before the orientation abbreviation represents the floor number. An office room (i.e. Zone '1W'), occupied by six persons was selected as the case room. The room floor area is 51.3 m^2, with 2.8 m height. The windows in the case room are the energy-efficient windows with a double pane construction made of 3 mm glass and a 13 mm argon gap. The window U-value is 1.062 W/(m^2·K), while the glass solar heat gain coefficient (SHGC) and visible transmittance are 0.579 and 0.698, respectively. To assume the similar conditions in all adjacent zones, the internal partitions between the case room and adjacent zones were set as adiabatic.

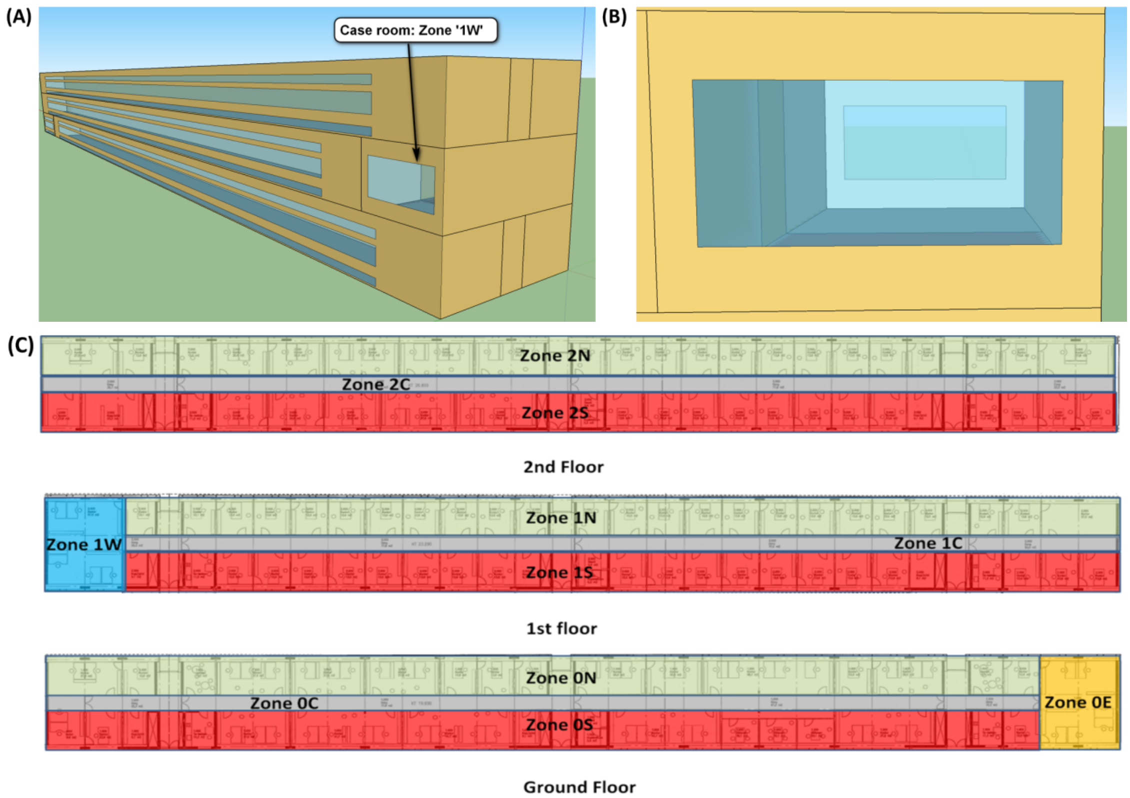

Figure 2. (A)(B) View of the building and case room, (C) layout of the case office building.

Typical meteorological year (TMY) data of Copenhagen, Denmark from the World Meteorological Organization was used in the simulation [33]. The summer season from 1 July to 1 September was chosen in this study. Figure 3 shows the direct solar radiation and outdoor air temperature of Copenhagen in the selected days. The daily mean ambient air temperature oscillated between 10.4 ºC and 21.7 ºC, while the daily maximum value of global horizontal solar irradiance varied between 9.2 W/m^2 and 790.8 W/m^2.

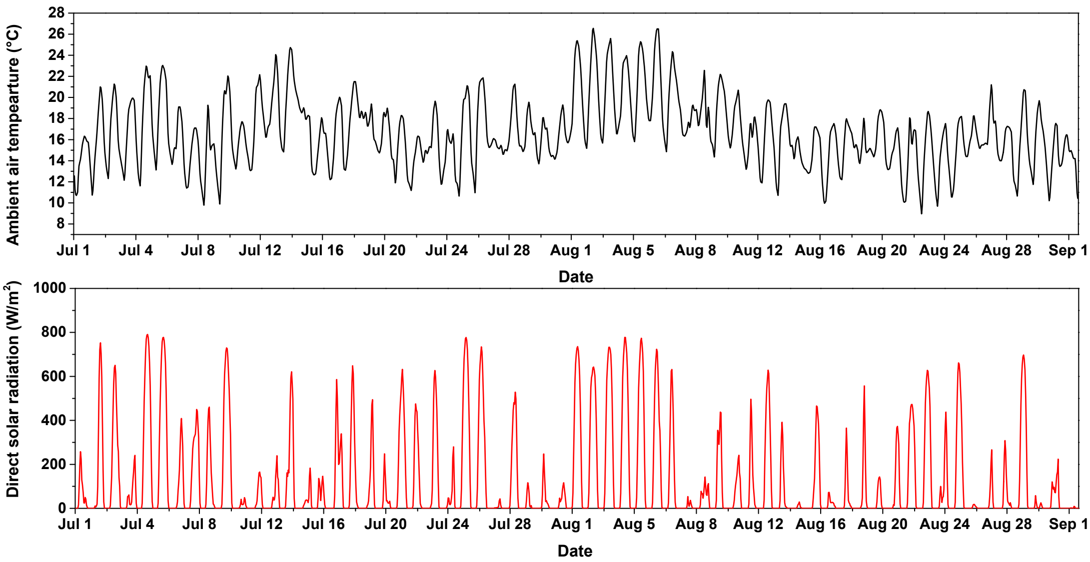

Figure 3. TMY weather data (outdoor temperature and direct solar radiation) of Copenhagen from 1 July to 1 September.

Table 1 shows the detailed thermophysical properties of construction elements. The internal thermal mass area is 20 m^2, while its density is 70 kg/m^2 of the net surface area which fulfills the reasonable range (i.e. 10–100 kg/m^2) for the internal thermal mass density in office buildings [34]. The last column of Table 1 is the total dynamic heat capacity per unit floor area (236.2 $kJ/m^2 \cdot K$), indicating that the case room has a heavy thermal mass level [35]. The dynamic heat capacity c_{dyn} defines how much energy can be stored per area if its surface is exposed to a sinusoidal temperature variation with a 24 h time-period [36].

The internal heat gains were set as people with a load of 120 W/person, lights with 6 W/m^2, and electric equipment with 8 W/m^2 [37]. The hourly operational schedules for the internal heat gains were 1.0 during the occupied hours (08:00-17:00) on weekdays while 0 for other hours. The people's clothing level was set at 0.5 clo in summer [38]. The air change rate of room infiltration was set as 0.5 h^{-1} [39].

Table 1. Thermophysical properties of building materials and detailed composition of the thermal mass.

	d (mm)	ρ (kg/m³)	c (J/kg/K)	λ (W/m·K)	Total (kJ/m²·K)	c_{dyn}/A_{floor}
External wall						
Plasterboard (fire-resisting)	160	900	1000	0.25		
Concrete 200	200	2385	800	1.2		
PUR 210	210	40	1400	0.021		
Cement plate	15	2000	1500	0.35		
Internal wall						
Gypsum board	25	1000	792	0.4		
Mineral wool	70	1750	1000	0.56		
Gypsum board	25	1000	792	0.4		
Ceiling						
Cast concrete 120	120	1800	1000	1.13	236.2	
Floor						
Linoleum	3	1200	1470	0.17		
Cement screed (fiber reinforced)	50	1400	1000	0.8		
Acoustic insulation	9	556	1700	0.15		
OSB panels	25	600	2150	0.13		
Insulation glass wool	200	28	1030	0.032		
Wooden panels	60	250	2100	0.047		
Internal thermal mass						
Cast concrete 100	100	1800	1000	1.13		

The cooling systems were daytime air conditioning and night ventilation. A packaged terminal air conditioner (AC) with a coefficient of performance (COP) 3.2 and a sizing factor 1.2 from the HVAC Template module of EnergyPlus was set in the case room. The AC temperature setpoint for cooling was set at 24.5 °C, while the outdoor airflow rate was 30 m^3/(h·person) [38]. The AC operated from 08:00-17:00 on weekdays from 1 July to 1 September. The NV system was a balanced system (i.e. a supply fan with an exhaust fan). A general scheme for NV was set as follows. The minimum indoor air temperature setpoint for night ventilation was 18 °C, to cool down the thermal mass efficiently and prevent the overcooling penalty [40]. Besides, the activation threshold temperature was 3 °C (i.e. night cooling only operated when the indoor air temperature exceeded the ambient temperature by 3 °C). The air change rate (ACH) setpoint of night cooling was 10 h^{-1}, which was the specified maximum air change rate [6]. It means that when the activation threshold temperature is met and minimum indoor air temperature is not violated, the fans will operate at the speed equivalent to 10 h^{-1} ACH; otherwise, the fans will stop. The night ventilation schedule was during 17:00-08:00 (+1) on weekdays from 1 July to 1 September. The '+1' in the parentheses means the next day. To investigate and optimize the NV performance with different SFPs, three SFPs were chosen which were 0, 0.5 and 1 kW/(m^3/s), representing the natural NV (Case 1), medium SFP mechanical NV (Case 2), and high SFP mechanical NV (Case 3), respectively. The SFPs all fulfilled the recommended 'good-practice' SFP for night cooling should not be higher than 1 kW/(m^3/s) based on the technical note AIVC 65 [41]. Table 2 lists the parameters related to NV.

Table 2. Parameters related to NV.

Parameter		Unit	Case 1	Case 2	Case 3
P1	Night venting duration	h	17:00-08:00	17:00-08:00	17:00-08:00
P2	Minimum indoor temperature setpoint	°C	18	18	18
P3	Night ACH setpoint	h^{-1}	10	10	10
P4	Activation threshold temperature	°C	3	3	3
P5	Internal thermal mass area	m^2	20	20	20
P6	Specific fan power (SFP)	kW/(m^3/s)	0	0.5	1

2.3 Global sensitivity analysis

Global sensitivity analysis methods can investigate the influences of all input parameters on output variables simultaneously, compared to screening methods and local sensitivity methods [42]. This paper adopted the most widely used global sensitivity analysis method, i.e. the regression method, to identify the key parameters related to NV performance on building energy/thermal performance. One reason is that this method is less computationally expensive and easy to understand. Another reason is that this method can avoid the drawbacks of local sensitivity analysis, which only explores a reduced space of the input factor around a base case, does not consider the interaction, and does not have self-verification. Several sensitivity indicators based on the regression method have been used in building energy analysis [27,43–45]. Standardized Rank Regression Coefficient (SRRC) with Monte Carlo analysis (MCA) was selected to quantify the impact of each parameter as it allowed the evaluation for non-linear but monotonic functions among inputs and outputs [45]. The SRRC is calculated by performing regression analysis on rank-transformed data (i.e. input parameters and output variables) rather than the raw data. The larger the absolute value of SRRC, the more influential the input parameter is. SRRC should be used when samples are generated with the LHS method which fully covers the range of each input parameter [46]. The sample size based on LHS was chosen to be 400 as the minimum size should be bigger than 10 times the number of input parameters [45]. SimLab generates the 400 samples based on the aforementioned method before sending them to jEPlus. Then, jEPlus generates building simulation model descriptions (jep file) based on the job list from SimLab to run the EnergyPlus and collects the results (cf. Figure 1). Finally, SimLab gets the results from jEPlus and conducts the sensitivity analysis by calculating the sensitivity measures (i.e. SRRC).

Table 3 shows the range and distribution of the independent parameters related to NV performance. Since the paper aims to quantify the effects of different building design options rather than exploring the possible range of thermal performance for an existing building, the distributions for these parameters should be uniform or discrete [42]. Because there are infinite possible time plans theoretically for night ventilation during 17:00-08:00 (+1), to simply quantify the order and size of the night venting duration, 15 time plans with 1-hour intervals were selected, representing the night venting duration ranging from 1 hour to 15 hours. The upper limit of minimum indoor temperature setpoint was chosen according to the design criteria of thermal conditions in summer in EN 15251 [38]. The upper limit of night ventilation ACH originated from the lowest temperature for cooling in the office room of category III in EN 15251 [38]. The upper limit of SFP was selected according to the technical note AIVC 65 that recommends 'good-practice' SFP for night cooling not exceeding 1 kW/(m^3/s) [41]. The total cooling energy consumption (TCEC) which included the energy consumption of AC plus NV and the average predicted percentage of dissatisfied during occupied hours of 08:00-17:00 (aPPD) were selected as the output variables for the evaluation of the building energy and thermal performance.

Table 3. Range and distribution of parameters related to NV performance.

Parameter		Unit	Range
P1	Night venting duration	h	**D** [(17:00-18:00), (17:00-19:00),…, (17:00-08:00)]
P2	Minimum indoor temperature setpoint	℃	**U** [18-22]
P3	Night ACH setpoint	h^{-1}	**U** [0-10]
P4	Activation threshold temperature	℃	**U** [1-3]
P5	Internal thermal mass area	m^2	**U** [0-40]
P6	Specific fan power (SFP)	kW/(m^3/s)	**U** [0-1]

Note: **D**: discrete distribution (levels); **U**: uniform distribution (lower value, upper value).

2.4 Omni-optimizer

This study uses omni-optimizer, an evolutionary optimization algorithm for single and multi-objective optimization that belongs to the category of generational genetic algorithms (GAs). Omni-optimizer originates from a widely used generic NSGA-II (Non-dominated sorting genetic algorithm II) algorithm that finds the Pareto optimal solutions for a multi-objective problem. Furthermore, it has high efficiency of adapting automatically to handle four types of optimization problems: ①Single-objective, uni-optimal; ②Single-objective, multi-optima; ③Multi-objective, uni-optimal optimization; ④Multi-objective, multi-optima optimization [47]. Omni-optimizer also integrates a high-efficiency constraint handling mechanism to process any amount of equality and inequality constraint conditions [48]. The constrained M-objective (M≥1) minimization problem can be posed mathematically as follows:

$$
\begin{aligned}
&\text{Minimize} && (f_1(\mathbf{x}),\ f_2(\mathbf{x}),\ldots,f_M(\mathbf{x})),\\
&\text{Subject to} && g_j(\mathbf{x}) \geq 0,\ j = 1, 2,\ldots, J,\\
& && h_k(\mathbf{x}) = 0,\ k = 1, 2,\ldots, K, \qquad (1)\\
& && x_i^{(L)} \leq x_i \leq x_i^{(U)}, i = 1, 2,\ldots,n.
\end{aligned}
$$

Where **x** is the solution vector and n is the number of decision variables. j and $g_j(\mathbf{x})$ are the numbers of inequality constraints and their vector, while k and $h_k(\mathbf{x})$ are the number of equality constraints and their vector, respectively. The solution vector **x** that satisfies all aforementioned constraints and variable bounds is regarded as a *feasible* solution. Mathematically, the optimality of a solution depends on a number of KKT (Karush–Kuhn–Tucker) optimality conditions which involve finding the gradients of objective and constraint functions [49]. This study aims at finding the minimum TCEC while maintaining the aPPD within a certain range, which belongs to the type 1 optimization problem as mentioned above.

3. Results and discussion

3.1 NV performance demonstration

Before the global sensitivity analysis and optimization, it is essential to reveal the NV mechanism and demonstrate the NV performance through the simulation. The base case is the building model introduced in Section 2.2 without NV. The NV case 2 (i.e. SFP of 0.5 kW/(m^3/s)) was selected for the NV performance demonstration.

Figure 4 shows the simulated data of zone air temperature, internal thermal mass surface temperature and hourly fan/AC energy consumption of the base case and case 2 in a typical summer day (July 29 to July 30). On the selected night (i.e. 17:00 to 08:00), the ambient air temperature fluctuated between 13.7 ºC to 16.9 ºC, which was very suitable for NV. The zone air and internal thermal mass surface temperatures of the base case varied slightly at night, remaining at about 27.8 ºC and 28.1 ºC, respectively. The reason is that the excess heat stored in the building elements at daytime was released which neutralized the heat loss through the building envelope. Whereas for case 2, due to the fans' operation, the zone air temperature and the internal thermal mass surface temperature were much lower than for the base case at night, and the maximum temperature differences can be 9.3 ºC and 7.4 ºC, respectively. The fan energy consumption at night was 2.7 kWh.

At 08:00 on July 30, the zone air temperatures of the base case and case 2 were 27.8 ºC and 19.4 ºC, respectively. Because the AC setpoint was 24.5 ºC, the AC began to work for the base case at 08:00, while AC was postponed to operate for the base case with NV until 12:45 by about 5 hours. Therefore, for the base case, the zone air temperature began to reach the AC setpoint after 08:00, while the internal thermal mass surface temperature continued to remain steady, presumably due to the energy balance between the heat gain of the internal thermal mass and the heat removed by the AC. However, for case 2, both the temperatures began to go up after 08:00. The zone air temperature rose faster than the internal thermal mass surface temperature and reached to AC setpoint after 12:45, while the surface temperature did not reach AC setpoint until 17:00. This was because the internal thermal mass was mainly heated by convection with room air, and thereby heating was delayed and happened after heating of the air. The AC daily energy consumption for the base case and case 2 was 6.2 kWh and 0.4 kWh, respectively, indicating that NV saved AC energy consumption. When the fan energy consumption at night was taken into consideration, the TCEC for case 2 was 3.1 kWh, which was 3.1 kWh lower than for the base case.

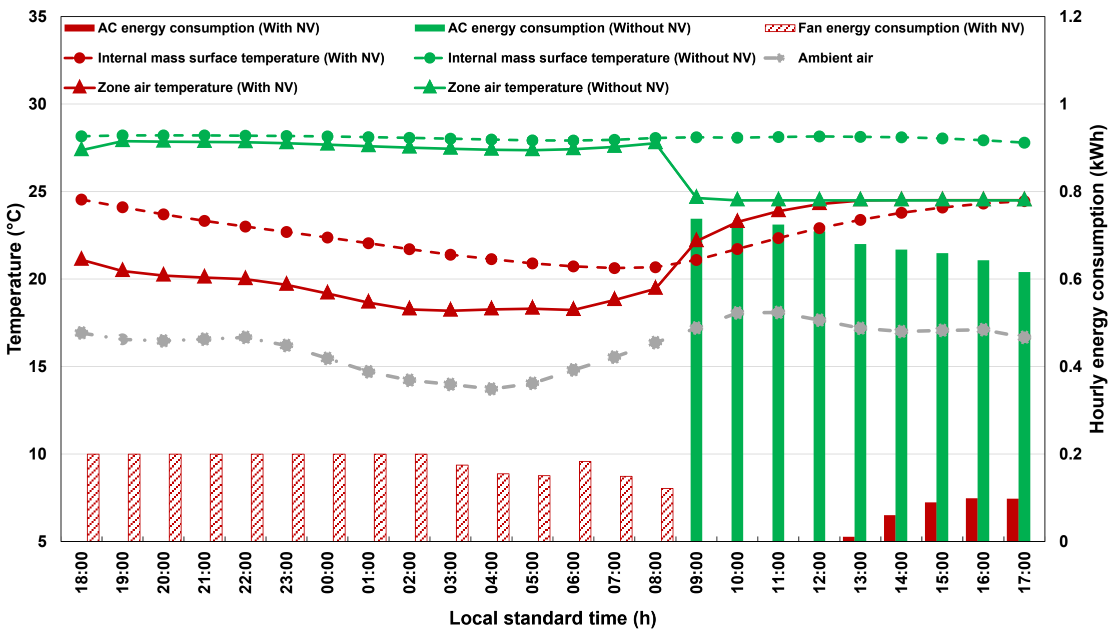

Figure 4. Comparison of zone temperatures and energy consumption of the base case and case 2 with NV in a typical summer day (July 29 to July 30).

Furthermore, the simulated data in Figure 5 shows that the PPD of the base case with NV was always higher than the base case (i.e. without NV), especially at the beginning of the occupied hours. The aPPD for case 2 with NV was 14.1%, 8.7% higher than the base case. The reason was that the NV with high ACH overcooled the indoor air and building elements in the cold climate region, resulting in an overcooling penalty that made people feel cold at the beginning of occupied hours.

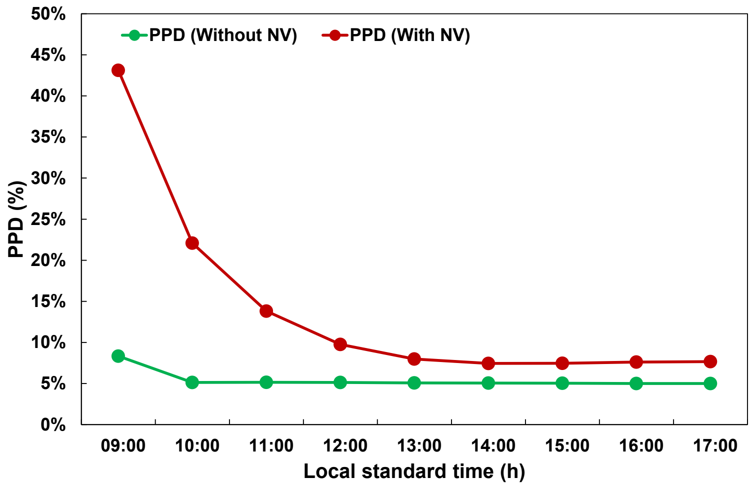

Figure 5. Comparison of PPD of the base case and case 2 at a typical summer daytime (July 30).

3.2 Influence of concerned parameters on building energy/thermal performance

Figure 6 illustrates the influence of the six parameters presented in Table 3 on the TCEC and aPPD. A larger absolute value of SRRC means the related parameter is more influential on the corresponding output. Besides, a positive sign of SRRC indicates that the output generally increases as the related input increases, while a negative sign of SRRC means that changes in the input and output tend to go in opposite directions [44]. Night venting duration is the most influential parameter on TCEC, followed by the night ventilation ACH, SFP, and internal thermal mass area. The minimum indoor air temperature setpoint and activation threshold temperature for night cooling activation have little influence on TCEC. The more night cooling (i.e. longer night venting duration and more ACH), the lower TCEC. On the contrary, increasing the SFP and internal thermal mass area tends to consume more TCEC.

For aPPD, night venting duration also has the greatest impact, followed by the internal thermal mass area, night ventilation ACH, and minimum temperature setpoint. The threshold temperature and SFP are not important parameters for the aPPD. Contrary to the impact of night cooling on TCEC, the more night cooling, the more aPPD. It indicates that more night cooling generally contributes to saving more TCEC by postponing or reducing the AC operation, but also results in the overcooling penalty at the beginning of the working day in the cold climate region. Adding the internal thermal mass area tends to reduce the aPPD while increasing the minimum temperature setpoint tends to affect the aPPD inversely. This is presumably because when NV cools a heavy thermal mass level sufficiently, it will remain at a low surface temperature for a longer time during occupied hours, thereby leading to a colder indoor thermal environment. Whereas a higher minimum temperature setpoint can reduce the risk of overcooling phenomena by NV and decrease the aPPD.

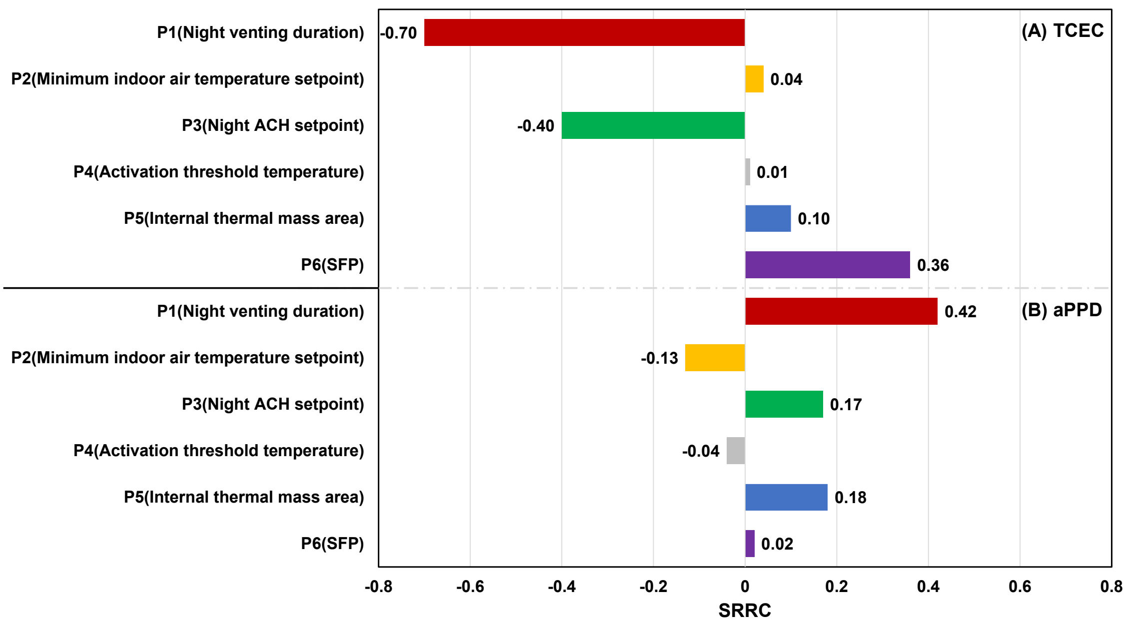

Figure 6. Standardized Rank Regression Coefficient (SRRC) of the concerned parameters.

3.3 Optimization

3.3.1 Optimization setup

The global sensitivity analysis in Section 3.1 manifested that the activation threshold temperature was not a key parameter. Hence, there was no need to optimize it, and it was kept at 3 °C. Besides, the SFP was not optimized as it was an intrinsic parameter once the fan was selected. Cases 1, 2, 3, and base case listed in Table 2 were selected to compare and optimize the NV performance. It is worth noticing that the airflow rate of natural NV is determined/influenced by many factors in real life, like the climate condition, window opening, building orientation, etc. This study focuses on optimizing the airflow rate at night and evaluating the influence of the optimal airflow rate on the building cooling energy and indoor thermal comfort; therefore, how using natural NV can achieve the optimal airflow rate is not an issue in this study. It is also worth noticing that even though the NV is equipped with the variable flow rate fan, it only operates at a constant airflow rate during the entire nighttime under the general scheme when the activation threshold temperature is met and minimum indoor air temperature is not violated. This is due to the lack of indoor air temperature setpoint, which cannot vary the airflow rate. The reason why there is no indoor air temperature setpoint is that the basic concept of NV is to utilize most of the cooling potential of ambient air when office buildings are not occupied.

The optimization aims at finding the optimal night ACH setpoint at each hour. Hence, the variable flow rate fan was selected. According to the technical note AIVC 65 [41], the SFP at each part-load operating point can be estimated as a function of the fraction of maximum flow rate (r) by the following generic equation for $0.2 \leq r \leq 1.0$:

$$\frac{SFP_{part\ load}}{SFP_{max\ load}} \approx a + br + cr^2 + dr^3 \qquad (1)$$

Figure 7 illustrates the different levels of the fan performance curve. The 'Good' performance curve was selected, which represents systems for which the fan pressure decreases with the airflow rate. The coefficients of *a*, *b*, *c,* and *d* for use in Eq. (1) were 0.5765, -1.5030, 2.6557, and -0.7292 respectively. The maximum SFPs for the medium SFP mechanical NV (Case 2), and high SFP mechanical NV (Case 3) were both at the maximum ACH of 10 h^{-1}. The fraction of maximum flow rate (r) at each hour for mechanical NV should be between 0.2 to 1.0 (i.e. ACH of 2 to 10 h^{-1}) or 0 (i.e. stop ventilation). While for natural NV, the fraction r was between 0 to 1.0 (i.e. ACH of 0 to 10 h^{-1}) at each hour for optimization.

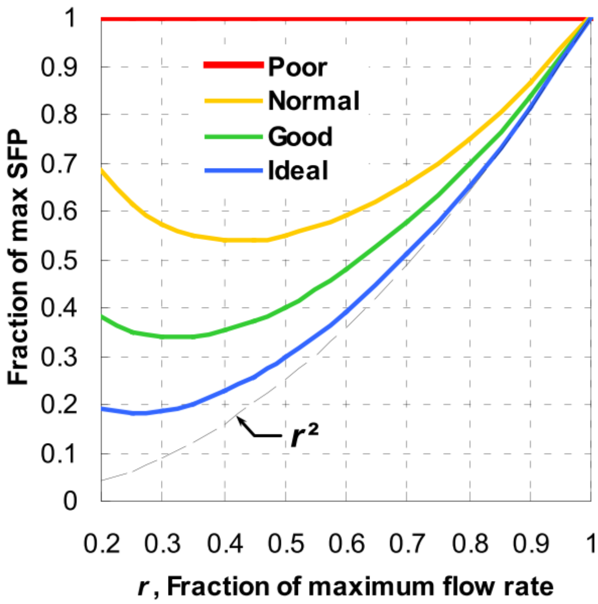

Figure 7. Illustration of Eq. (1) for Poor, Normal, Good, and Ideal systems [41].

To reduce the computational effort and staying close to reality, discrete distributions rather than continuous distributions were selected. Several simplifications and modifications were conducted to improve the simulation and optimization speed:

1) The night ventilation ACH setpoint between 17:00-08:00 (+1) at each 1 hour was optimized with a discrete variable from 0 to 10 h^{-1} with a step of 0.1 h^{-1} for natural NV, while 0 or 2 to 10 h^{-1} with a step of 0.1 h^{-1} for mechanical NV,

2) The internal thermal mass area was optimized with a discrete variable ranging from 0 to 40 m^2 with a step of 0.1 m^2, and

3) The minimum indoor temperature setpoint was optimized with a discrete variable from 18 to 22 ℃ with a step of 0.1 ℃.

Table 5 lists the parameters for cases 1, 2, 3, and base case, while Table 4 summarizes the parameters to be optimized for cases 1, 2, and 3. The population size, maximum generation number, mutation probability, and crossover number, were set as 16, 150, 0.167, and 0.9 respectively by compromising the computational effort and the accuracy [50].

Table 4. Range and distribution of parameters for NV optimization of cases 1, 2, and 3.

Parameter		Unit	Range
O1	Night ventilation ACH setpoint	h^{-1}	**D** [0-10] with step 0.1 h^{-1} at each hour for natural NV **D** 0 or [2-10] with step 0.1 h^{-1} at each hour for mechanical NV
O2	Minimum indoor temperature setpoint	℃	**D** [18-22] with step 0.1 ℃
O3	Internal thermal mass area	m^2	**D** [0-40] with step 0.1 m^2

Note: **D**: discrete distribution (levels);

This study aims at minimizing the TCEC while maintaining the aPPD at a certain range. Furthermore, different constraint levels can be selected, according to the recommended categories of PPD for the design of mechanical cooled buildings in EN 15251 [38]. This study aims at maintaining the same thermal comfort level as in the base case (i.e. the basic building without NV). The simulated aPPD of the base case during the whole simulation period was 7.5%; this was selected as the constraint. Therefore, the optimization problem can be formulated as:

$$\min \; TCEC = C_{AC} + C_{NV} \tag{2}$$

$$\text{subject to} \qquad aPPD < 7.5\% \tag{3}$$

where C_{AC} and C_{NV} stand for the AC energy consumption at daytime and NV energy consumption at night, respectively.

3.3.2 Optimization results

Figure 8 integrates the solutions during the optimization procedure by the omni-optimizer for cases 1, 2, and 3. For the single-objective minimization with the constraint problem, the omni-optimizer utilized the penalty-parameter-less approach to put two solutions in the constrained-tournament selection operator proposed in [51] to determine if a solution is better than the other. The above selection operator fulfilled the following criteria: 1) A feasible solution was always better than an infeasible solution, 2) A feasible solution with better objective function value was preferred to another feasible solution, and 3) An infeasible solution with smaller constraint violation was better than another infeasible solution. Apart from the dominated solutions of three cases, the non-dominated solutions in each case fulfill the Pareto front, which is similar to the multi-objective optimization. It reveals the conflict between the two indicators.

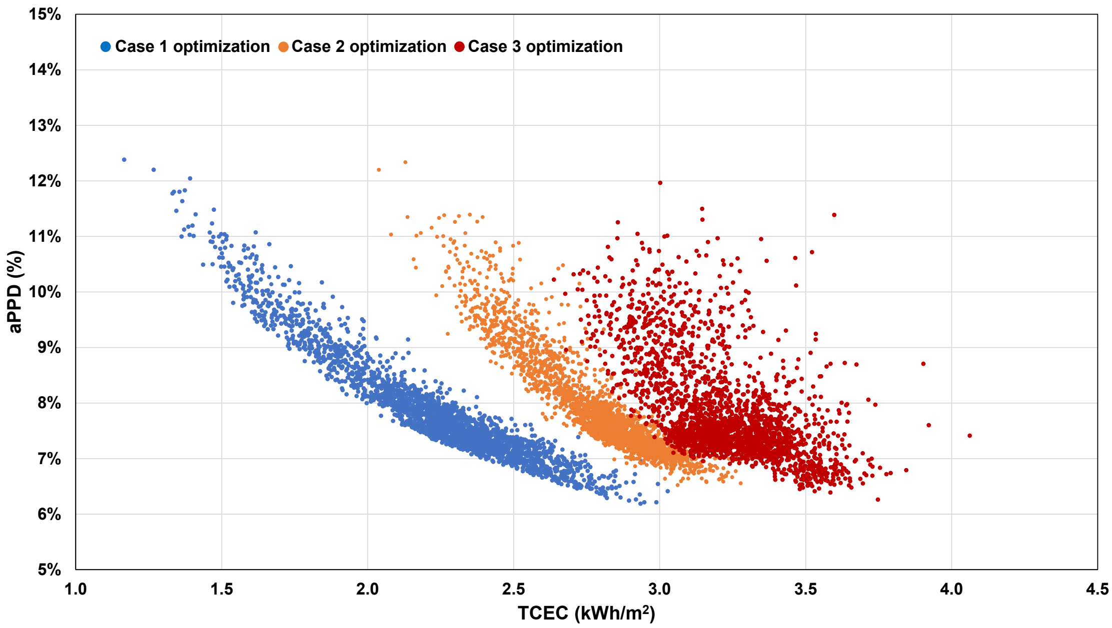

Figure 8. Optimized solutions for cases 1, 2, and 3.

Figure 9 shows the simulated aPPD and TCEC of the research cases. When the base case is equipped with different SFPs NV (i.e. cases 1, 2, 3), the TCEC significantly decreases by 0.5 kWh/m^2 (8.8%) to 4.7 kWh/m^2 (82.5%). Even the high SFP mechanical NV can save 8.8% TCEC compared to the base case. However, adopting NV with a general scheme worsens the indoor thermal comfort by increasing the aPPD from 7.5% to about 15%. After the optimization, all three optimal cases improve the indoor thermal comfort and fulfill the constraint (i.e. aPPD less than 7.5%). The optimal cases 2 and 3 further save 0.4 kWh/m^2 (7.1%) and 2.2 kWh/m^2 (38.6%) TCEC of the cases 2 and 3, respectively. It means that a higher SFP yields a greater total cooling energy-saving potential by optimization. Even though the optimal case 1 consumes 1.2 kWh/m^2 more TCEC than case 1, it is still worthy optimizing the natural NV as the overcooling penalty is avoided and the optimal natural NV still saves much TCEC compared to the base case.

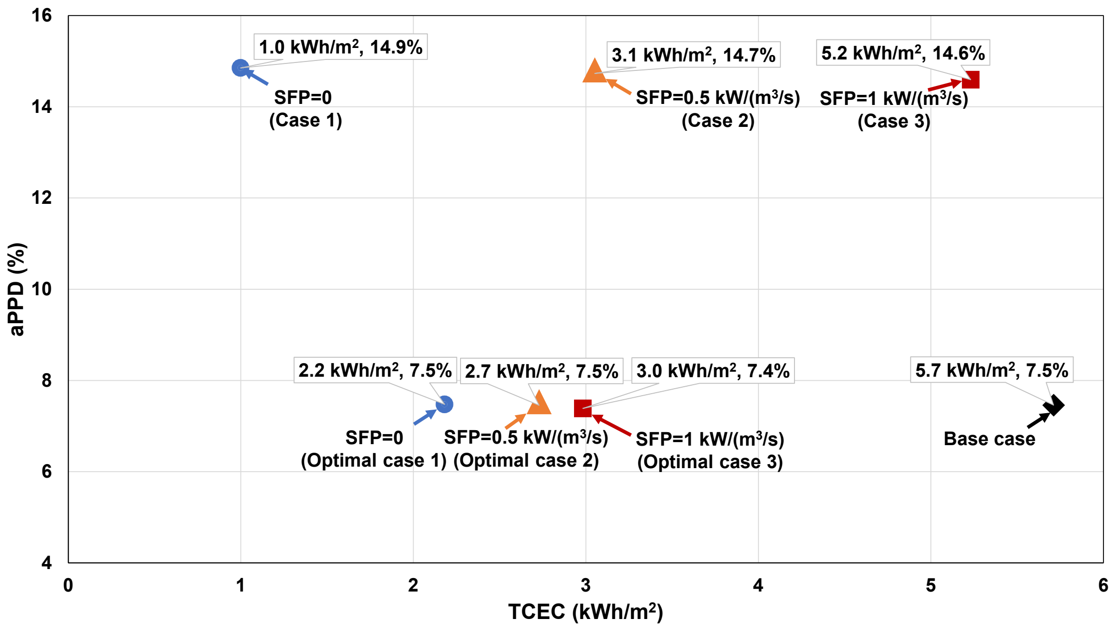

Figure 9. The values of TCEC and aPPD of the research cases.

Figure 10 shows the parameters of the research cases. The area and temperature in the parentheses of the legend are the internal thermal mass area and minimum indoor air temperature setpoint of the corresponding case. The value in the Y-axis represents the night ACH setpoint at each hour. Compared to cases 1, 2, 3, the internal thermal mass areas and night ACH setpoint at each hour of the optimal cases are smaller, but the minimum indoor air temperature setpoints of the optimal cases are higher. The optimal internal thermal mass areas are reduced to 8.7 to 10.4 m^2, which is equivalent to 22.1 to 26.4 $kJ/m^2{\cdot}K$ dynamic heat capacity per unit floor area (c_{dyn}/A_{floor}) reduction. The optimal minimum indoor air temperature setpoints vary from 21.2 ºC to 21.6 ºC. The optimal minimum indoor air temperature setpoints are close to the upper limit (i.e. 22 ºC) of this parameter setup, which indicates this setpoint values should not be too low in the cold climate region. There is no big difference between the two optimal parameters mentioned above among the three optimal cases.

However, the optimal night ACH setpoints at each hour during the night are very different from each other. However, all of them are less than 10 h^{-1} of cases 1, 2, and 3. All the optimal cases tend to decrease the night ACH setpoint severely before the occupied hours. Figure 11 illustrates the average night ACH for different cases. The average night ACHs of optimal cases decrease by 4.1 h^{-1} to 5.2 h^{-1}, compared to cases 1, 2, and 3. The average night ACH of optimal case 3 is the lowest among the three optimal cases, while that of the optimal case 1 is the highest. The average night ACHs of cases 1, 2, and 3 are a little different and are not equal to the setpoint of 10 h^{-1}. One reason is that the room inlet air at night can be heated by the intake fan power that will influence the zone air temperature to some extent. In consequence, the case 3 with a higher SFP needs more night cooling. Another reason is that the threshold temperature (i.e. 3 ºC) of NV stops the ventilation when the temperature difference between indoor and outdoor air is not met.

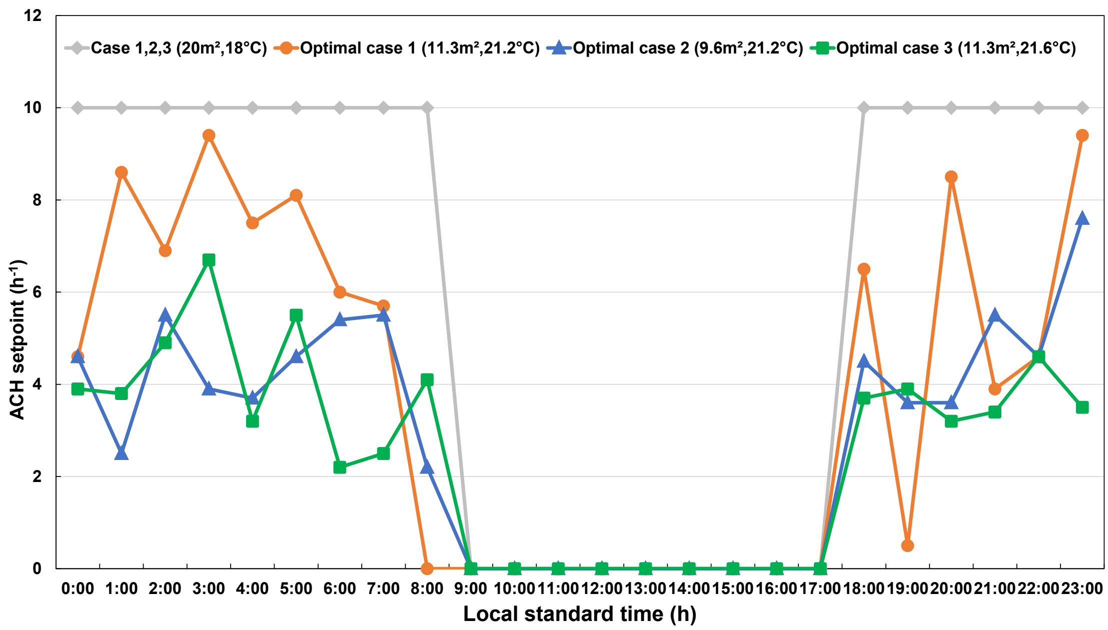

Figure 10. Parameters related to NV of the research cases.

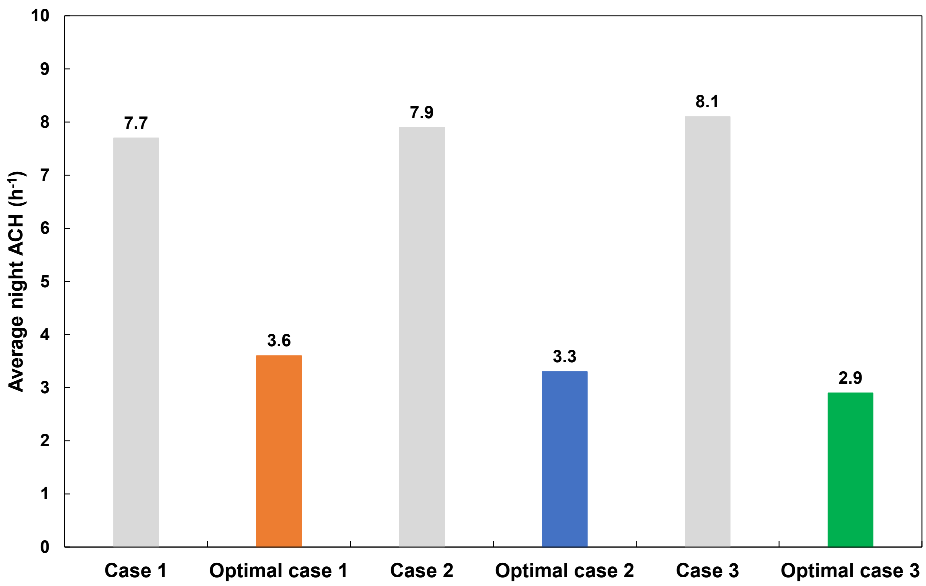

Figure 11. Average night ACH of the research cases.

4. Limitations and prospect

From the authors' perspective, current limitations can be described as follows:

- This study optimized different parameters based on the TMY data, especially the night ACH setpoint at each hour. It may result in the NV performance of certain days under real weather conditions deviating from expectations or not as good as the case adopting the advanced adaptive control algorithm like weather predictive control or model predictive control.
- Natural NV was simplified in this study, which was inherently unstable and highly dependent on the local climate condition, building orientation, window size or window automation system, etc. The expected night ACH for the optimal natural NV may not be fulfilled with the real natural NV system under the real circumstance. However, this study has the potential/ability to optimize the hourly opening availability of windows and ventilation control zone temperature setpoint of a real natural NV system modeled with the AirflowNetwork model in EnergyPlus under the same objective and constraint. It should be noticed that even

optimizing the control parameters of a real natural NV may still not fulfill the optimal natural ACH shown in this study. Because the actual possibility to reach the optimal ACH also depends on the architectural design, the building location, and the local wind environment that were not included in this study.

- Only a single case room was optimized in this study. One reason was that this study devoted to putting forward a method/ability to optimize the NV performance, which was also applicable for multiple rooms or the whole building. Another reason was to reduce the computation time and analyze the optimal results easier and clearer. It is worth noticing that even though the optimal solutions of different rooms or the whole building may differ, the optimal result (i.e. TCEC and aPPD) or trend was also applicable for other cases. As the heat gain of the case room should be much higher than other rooms, but this room still met the overcooling penalty under the high-ACH scenario. Therefore, the same problem will occur in other rooms. Under the same objective and constraint with the omni-optimizer, similar optimal results are expected for other rooms or the whole building.

Overall, the key to obtaining the best NV performance was the match between the cooling potential of NV and the excess heat stored/ released in thermal mass. This study proposed a generic evolutionary algorithm to find that 'match' in the approximate infinite combinations, compared to the finite combinations of NV optimization [9][10][52]. Different from the aforementioned advanced control algorithms that generally manipulate a single variable and optimize the building performance based on a given building, this method focused more on guiding engineers or designers at the early building design stage. Furthermore, models identified through the mathematical method from the real building operation data for advanced control algorithms can only maintain the indoor air temperature rather than more precise thermal comfort indicators (e.g. PMV, PPD) within a certain range [53].

Apart from the optimization of the thermal mass amount in this study, the method is also flexible to investigate the optimal parameters related to the excess heat storage and release in the thermal mass; for instance, the insulation level, internal heat gain, thermal mass material (e.g. PCM), daytime cooling methods or related control parameters, etc. As alluded to above, the omni-optimizer has a high efficiency to adapt automatically to handle four types of optimization problems, which can fulfill the different requirements of research and design. The objective or constraint can also be selected based on the research/design purpose. For example, the objective can be to minimize the energy cost based on the real electricity price or utility rate.

5. Conclusion

This study proposes a systematic approach to optimize the NV performance in terms of energy use and thermal comfort. The case study is a three-story office building equipped with daytime air conditioning and an NV system in Aarhus, a city in a cold climate region in Denmark. An NV performance simulation is conducted to demonstrate the NV mechanism. Then, a global sensitivity analysis is carried out to explore the impact of night venting duration, minimum indoor temperature setpoint, night ACH setpoint, activation threshold temperature, and internal thermal mass area and SFP on NV performance. The key design parameters are then optimized based on an evolutionary algorithm to minimize total cooling energy consumption while maintaining the indoor thermal comfort within a reasonable range. Based on the results of the case study, the following conclusions can be made.

- A medium SFP NV with a general scheme can reduce the zone air temperature and internal thermal mass surface temperature by up to 9.3 ºC and 7.4 ºC, respectively on a typical summer day. It can also postpone the air conditioner operation for about 5 hours and save 3.1 kWh TCEC compared to the case without NV. However, by increasing aPPD from 5.1% to 14.1% on the selected day, the NV may overcool the indoor air and building elements to worsen the indoor thermal comfort.

- For TCEC, night venting duration is the most influential parameter, followed by the night ventilation ACH, SFP, and internal thermal mass area. While for aPPD, night venting duration also has the greatest impact, followed by the internal thermal mass area, night ventilation ACH, and minimum temperature setpoint. Activation threshold temperature is an insignificant parameter for NV performance.
- Different SFPs NV under a general scheme saves TCEC by 0.5 kWh/m^2 (8.8%) to 4.7 kWh/m^2 (82.5%) compared to the base case but increases the aPPD from 7.5% to about 15%. After the optimization, all the optimal cases improve the indoor thermal comfort and fulfill the constraint of 7.5%. The optimal medium and high SFP mechanical NV further save 0.4 kWh/m^2 (7.1%) and 2.2 kWh/m^2 (38.6%) TCEC respectively, compared to the corresponding case without optimization. The higher the SFP, the greater the saving potential of TCEC by optimization. Even though the optimal natural NV consumes more than twice as much TCEC as the case without optimization, the natural NV still deserves optimization as the overcooling penalty is avoided and the optimal natural NV still saves more TCEC compared to the case without NV.
- The optimal cases reduce 8.7 to 10.4 m^2 internal thermal mass area compared to the cases without optimization, which is equivalent to 22.1 to 26.4 kJ/m^2·K dynamic heat capacity per unit floor area reduction. The optimization elevates the

minimum indoor air temperature setpoint to 21.2 ºC to 21.6 ºC. There is no much difference between the two optimal parameters mentioned above between the three optimal cases. However, the optimal night ACH setpoints at each hour at night are much different from each other, but both less than 10 h^{-1} of the corresponding case without optimization.

6. Acknowledgment

The project is carried out as part of IEA EBC Annex 80 Resilient Cooling. The first author gratefully acknowledges the financial support from the Chinese Scholarship Council (CSC No. 201706050001).

7. Reference

[1] Kolokotroni M, Heiselberg P. Ventilative Cooling: State-of-the-Art Review. Aalborg Univ Aalborg, Denmark 2015.

[2] Santamouris M. Cooling the buildings – past, present and future. Energy Build 2016;128:617–38. doi:10.1016/j.enbuild.2016.07.034.

[3] Artmann N, Manz H, Heiselberg P. Climatic potential for passive cooling of buildings by night-time ventilation in Europe. Appl Energy 2007;84:187–201. doi:10.1016/j.apenergy.2006.05.004.

[4] Santamouris M, Kolokotsa D. Passive cooling dissipation techniques for buildings and other structures: The state of the art. Energy Build 2013;57:74–94. doi:10.1016/j.enbuild.2012.11.002.

[5] Solgi E, Hamedani Z, Fernando R, Skates H, Orji NE. A literature review of night ventilation strategies in buildings. Energy Build 2018;173:337–52. doi:10.1016/j.enbuild.2018.05.052.

[6] O'Donnavan A, Belleri A, Flourentzou F, Zhang G-Q, da Graca GC, Breesch H, et al. Ventilative Cooling Design Guide: Energy in Buildings and Communities Programme. March 2018. Aalborg University, Department of Civil Engineering; 2018.

[7] Liu J, Liu Y, Yang L, Liu T, Zhang C, Dong H. Climatic and seasonal suitability of phase change materials coupled with night ventilation for office buildings in Western China. Renew Energy 2019;147:356–73. doi:10.1016/j.renene.2019.08.069.

[8] Roach P, Bruno F, Belusko M. Modelling the cooling energy of night ventilation and economiser strategies on façade selection of commercial buildings. Energy Build 2013;66:562–70. doi:10.1016/j.enbuild.2013.06.034.

[9] Wang Z, Yi L, Gao F. Night ventilation control strategies in office buildings. Sol Energy 2009;83:1902–13. doi:10.1016/j.solener.2009.07.003.

[10] Wu L-X, Zhao J-N, Wang Z-J. Night ventilation and active cooling coupled operation for large supermarkets in cold climates. Energy Build 2006;38:1409–16. doi:10.1016/J.ENBUILD.2006.02.011.

[11] Kolokotroni M, Aronis A. Cooling-energy reduction in air-conditioned offices by using night ventilation. Appl Energy 1999;63:241–53. doi:10.1016/S0306-2619(99)00031-8.

[12] Vidrih B, Arkar C, Medved S. Generalized model-based predictive weather control for the control of free cooling by enhanced night-time ventilation. Appl Energy 2016;168:482–92. doi:10.1016/j.apenergy.2016.01.109.

[13] Dovrtel K, Medved S. Weather-predicted control of building free cooling system. Appl Energy 2011;88:3088–96. doi:10.1016/j.apenergy.2011.03.010.

[14] Braun JE, Zhong Z. Development and evaluation of a night ventilation precooling algorithm. HVAC R Res 2005;11:433–58. doi:10.1080/10789669.2005.10391147.

[15] Olsthoorn D, Haghighat F, Moreau A, Lacroix G. Abilities and limitations of thermal mass activation for thermal comfort, peak shifting and shaving: A review. Build Environ 2017;118:113–27. doi:10.1016/J.BUILDENV.2017.03.029.

[16] Farid MM, Khudhair AM, Razack SAK, Al-Hallaj S. A review on phase change energy storage: Materials and applications. Energy Convers Manag 2004. doi:10.1016/j.enconman.2003.09.015.

[17] Souayfane F, Fardoun F, Biwole PH. Phase change materials (PCM) for cooling

applications in buildings: A review. Energy Build 2016;129:396–431. doi:10.1016/j.enbuild.2016.04.006.

[18] Akeiber H, Nejat P, Majid MZA, Wahid MA, Jomehzadeh F, Zeynali Famileh I, et al. A review on phase change material (PCM) for sustainable passive cooling in building envelopes. Renew Sustain Energy Rev 2016;60:1470–97. doi:10.1016/j.rser.2016.03.036.

[19] Pomianowski M, Heiselberg P, Zhang Y. Review of thermal energy storage technologies based on PCM application in buildings. Energy Build 2013;67:56–69. doi:10.1016/j.enbuild.2013.08.006.

[20] Solgi E, Fayaz R, Kari BM. Cooling load reduction in office buildings of hot-arid climate, combining phase change materials and night purge ventilation. Renew Energy 2016;85:725–31. doi:10.1016/j.renene.2015.07.028.

[21] Solgi E, Kari BM, Fayaz R, Taheri H. The impact of phase change materials assisted night purge ventilation on the indoor thermal conditions of office buildings in hot-arid climates. Energy Build 2017;150:488–97. doi:10.1016/j.enbuild.2017.06.035.

[22] Yanbing K, Yi J, Yinping Z. Modeling and experimental study on an innovative passive cooling system - NVP system. Energy Build 2003. doi:10.1016/S0378-7788(02)00141-X.

[23] Shaviv E, Yezioro A, Capeluto IG. Thermal mass and night ventilation as passive cooling design strategy. Renew Energy 2001;24:445–52. doi:10.1016/S0960-1481(01)00027-1.

[24] Nguyen AT, Reiter S, Rigo P. A review on simulation-based optimization methods applied to building performance analysis. Appl Energy 2014;113:1043–58. doi:10.1016/j.apenergy.2013.08.061.

[25] Artmann N, Manz H, Heiselberg P. Parameter study on performance of building cooling by night-time ventilation. Renew Energy 2008;33:2589–98. doi:10.1016/j.renene.2008.02.025.

[26] Kolokotroni M, Webb BC, Hayes SD. Summer cooling with night ventilation for office buildings in moderate climates. Energy Build 1998;27:231–7. doi:10.1016/s0378-7788(97)00048-0.

[27] Guo R, Hu Y, Liu M, Heiselberg P. Influence of design parameters on the night ventilation performance in office buildings based on sensitivity analysis. Sustain Cities Soc 2019;50:101661. doi:10.1016/j.scs.2019.101661.

[28] EU Science Hub. SimLab v2.2 2008.

[29] Zhang Y, Korolija I. jEPlus-An EnergyPlus simulation manager for parametrics 2016.

[30] Department of Energy U. EnergyPlus, Simulation Program v8.9 2017. https://energyplus.net/documentation.

[31] Palonen M, Hamdy M, Hasan A. Mobo a new software for multi-objective building performance optimization. Proc. BS 2013 13th Conf. Int. Build. Perform. Simul. Assoc., 2013, p. 2567–74.

[32] Liu M, Heiselberg P. Energy flexibility of a nearly zero-energy building with weather predictive control on a convective building energy system and evaluated with different metrics. Appl Energy 2019;233–234:764–75. doi:10.1016/j.apenergy.2018.10.070.

[33] WMO Country Profile Database. World Meteorological Organization 2018. https://www.wmo.int/cpdb/.

[34] Johra H, Heiselberg P. Influence of internal thermal mass on the indoor thermal dynamics and integration of phase change materials in furniture for building energy storage: A review. Renew Sustain Energy Rev 2017;69:19–32. doi:10.1016/j.rser.2016.11.145.

[35] ISO EN. 13790: Energy performance of buildings–Calculation of energy use for space heating and cooling (EN ISO 13790: 2008). Eur Comm Stand (CEN), Brussels 2008.

[36] EN ISO 13786. Thermal performance of building components – Dynamic thermal characteristics – Calculation methods 2017.

[37] Guo R, Hu Y, Liu M, Heiselberg P. Optimal Night Mechanical Ventilation control strategy in office buildings. IOP Conf. Ser. Mater. Sci. Eng., vol. 609, IOP Publishing; 2019, p. 032013. doi:10.1088/1757-899X/609/3/032013.

[38] EN 15251. Indoor environmental input parameters for design and assessment of

energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics 2007.

[39] EN 16798-3. Energy performance of buildings – Ventilation for buildings – Part 3: For non-residential buildings – Performance requirements for ventilation and room-conditioning systems (Modules M5-1, M5-4) 2017.

[40] J MA. Control of natural ventilation. 1995.

[41] International Energy Agency. Technical note AIVC 65 - Recommendations on specific fan power and fan system efficiency. 2009.

[42] Wei T. A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 2013;20:411–9. doi:10.1016/j.rser.2012.12.014.

[43] Lim H, Zhai Z (John). Influences of energy data on Bayesian calibration of building energy model. Appl Energy 2018;231:686–98. doi:10.1016/j.apenergy.2018.09.156.

[44] Yildiz Y, Korkmaz K, Göksal özbalta T, Durmus Arsan Z. An approach for developing sensitive design parameter guidelines to reduce the energy requirements of low-rise apartment buildings. Appl Energy 2012;93:337–47. doi:10.1016/j.apenergy.2011.12.048.

[45] European Commission - IPSC. Simlab 2.2: Reference Manual 2008.

[46] Helton JC, Davis FJ. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. Reliab Eng Syst Saf 2003. doi:10.1016/S0951-8320(03)00058-9.

[47] Deb K, Tiwari S. Omni-optimizer: A generic evolutionary algorithm for single and multi-objective optimization. Eur J Oper Res 2008;185:1062–87. doi:10.1016/j.ejor.2006.06.042.

[48] Wang L, Wu J, Wang T, Han R. An optimization method based on random fork tree coding for the electrical networks of offshore wind farms. Renew Energy 2020;147:1340–51. doi:10.1016/j.renene.2019.09.100.

[49] Deb K. Optimization for engineering design: Algorithms and examples. PHI Learning Pvt. Ltd.; 2012.

[50] Palonen M, Hasan A. MOBO Beta 0.3 b Maunal Version 1.4 2014.

[51] Deb K. An efficient constraint handling method for genetic algorithms. Comput Methods Appl Mech Eng 2000. doi:10.1016/S0045-7825(99)00389-8.

[52] Ran J, Tang M. Passive cooling of the green roofs combined with night-time ventilation and walls insulation in hot and humid regions. Sustain Cities Soc 2018;38:466–75. doi:10.1016/j.scs.2018.01.027.

[53] Thieblemont H, Haghighat F, Ooka R, Moreau A. Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the art. Energy Build 2017;153:485–500. doi:10.1016/j.enbuild.2017.08.010.

Conflict of interest statement:

None

Rui Guo: Conceptualization, Software, Data curation, Investigation, Methodology, Writing - original draft, Writing - review & editing.

Per Kvols Heiselberg: Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

Yue Hu: Visualization, Writing - review & editing.

Chen Zhang: Visualization, Formal analysis, Writing - review & editing.

Sandijs Vasilevskis: Visualization, Formal analysis, Writing - review & editing.

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:
